MOD15 LAI/FPAR
ALGORITHM THEORETICAL BASIS DOCUMENT

MODIS LAI (LEAF AREA INDEX)
and
MODIS FPAR
(FRACTION of ABSORBED PHOTOSYNTHETICALLY ACTIVE RADIATION)

by

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ATBD-LAI/FPAR

MODIS FPAR AND LAI PRODUCTS ALGORITHM TECHNICAL BASIS DOCUMENT

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1.0 INTRODUCTION

This ATBD will describe our terrestrial leaf area index (LAI) product, and the related fraction of absorbed photosynthetically active radiation (FPAR) product. LAI defines an important structural property of a plant canopy, the number of equivalent layers of leaves vegetation displays relative to a unit ground area. FPAR measures the proportion of available radiation in the specific photosynthetically active wavelengths of the spectrum 0.4 - 0.7 μm that a canopy absorbs. It is non-linearly related to the LAI. Both LAI and FPAR will be Level 4 MODIS products, derived directly from MODIS Reflectances (MR) and ancillary data on surface characteristics such as Land cover type, background etc. These products will be produced globally at a time frequency defined by the MODIS Reflectances (MR) global compositing period, we assume here 8 days. The spatial resolution will be constrained by the MODIS reflectance dataset, and may be as fine as 250m, or standardized to 1km.

1.1 IDENTIFICATION

Leaf Area Index (LAI), MOD15 Parameter 2680 Fraction of Absorbed Photosynthetically Active Radiation (FPAR), MOD15 Parameter 5367

1.2 DESCRIPTION OF PRODUCTS

Because LAI most directly quantifies the plant canopy structure, it is highly related to a variety of canopy processes, such as interception, evapo-transpiration, photosynthesis, respiration and leaf litter-fall. LAI is an abstraction of a canopy structural property, a dimensionless variable that ignores canopy detail such as leaf angle distribution, canopy height or shape. Hence the definition of LAI is used by terrestrial models to quantify the above ecosystem processes. FPAR is a radiation term, so it is more directly related to remotely sensed variables such as Simple Ratio, NDVI etc. than LAI. FPAR is frequently used to translate direct satellite data such as NDVI into simple estimates of primary production. It does not define plant canopies as directly as LAI, but is more specifically related to the satellite indices. Because the interrelationships between LAI and FPAR is high, and the utility of each is high we plan to produce both. Neither LAI or FPAR are critical variables themselves, rather they are both essential intermediate variables used to calculate terrestrial energy, carbon, water cycling processes and bio-geochemistry of vegetation. The current consensus is that LAI will be used preferentially by ecological and climate modelers who desire a representation of canopy structure in their models. FPAR will be preferentially used by remote sensing scientists to interpret satellite data, and projects interested in simple direct estimates of photosynthetic activity and primary production without using mechanistic biome models. Much of the ambiguity involved in using either LAI or FPAR in global scale models can be eliminated if one also knows some general details about the basic life form of the vegetation, i.e. whether it is forest, grass, crop etc. Then certain assumptions about leaf angle distribution, basic leaf optical properties and clump leaf area index can be made to generate the relationships vegetation indices and LAI, and FPAR. We plan as part of the MODIS Land cover product to build a system that identifies these basic plant life forms globally, and can be used to pre-stratify further analyses of canopy biophysical properties.

2.0 OVERVIEW AND BACKGROUND

2.1 LAI

Plant canopies are the critical interface between the atmosphere and the terrestrial biosphere. Exchanges of energy, mass and momentum between the atmosphere and vegetation are controlled by plant canopies. Of particular importance are the gas exchange processes for CO_2 and H_2O, evapo-transpiration and photosynthesis. When considering the array of global vegetation, there is an infinite variety of plant canopy shapes, sizes and attributes. Over the last few decades, ecologists have found that a useful way to quantify plant canopies in a simple yet powerful way is by defining the leaf area index. This parameter represents the structural characteristic of primary importance, the basic size of the canopy, while conveniently ignoring the complexities of canopy geometry that make global comparisons impossible otherwise. As remote sensing became an important tool in ecology, initial efforts concentrated on measuring LAI by satellite (Asrar et al., 1984; Peterson et al., 1987).

Although the NPP of grasslands, annual crops and other seasonal biome types can be estimated by the time integration of observed developing biomass, for biome types such as forests, chapparal and other evergreen vegetation, permanent live biomass occupies the site continuously, causing annual NPP to not be visible from an orbiting satellites. For these biomes with continuous leaf display, a structural variable related to CO_2 exchange and comparable across biomes was required. LAI (the projected leaf area per unit ground area) provides a measure of the plant organ most directly involved in energy, H_2O and CO_2 exchange. Characterization of vegetation in terms of LAI, rather than species composition, was considered a critical simplification for comparison of different terrestrial ecosystems worldwide. Ecosystem analyses conducted during the International Biological Program of the 1970s had found strong correlations across biome types relating LAI to NPP (Gholz 1982, Webb et al., 1983). A functional balance between site water availability and LAI was also found (Grier and Running 1977), and Jarvis and McNaughton (1986) showed how evapo-transpiration (ET) is directly proportional to LAI. This logic isolated an initial specific task in global ecology, to develop means of measuring LAI of natural vegetation by satellite. Remote sensing of LAI was first attempted for crops and grasslands, correlating spectral reflectances against direct measurement of vegetation LAI. Various combinations of near-infrared and visible wavelengths have been used to estimate the LAI of wheat (Wiegand et al., 1979, Asrar et al., 1984). However, for global applications the complexities of natural, irregular canopies must be addressed. Peterson et al., (1987) first estimated the LAI of coniferous forests across an environmental gradient in Oregon using airborne Thematic Mapper Simulator data. A growing season site water balance ranging from +20 cm (surplus) on the Pacific coast to -80 cm water (deficit) in the interior desert produces LAI ranging from 1 - 6 (projected), representing the global range of forest LAI. This work was extended to California, Montana, Washington coniferous forests using Landsat TM data. Spanner et al. (1990) found that the strong relationships between TM NIR/RED ratios and LAI in closed canopy, pure conifer forests of Oregon, and these relationships can erode in forests with mixed deciduous canopy and/or soil surface exposed. Remote sensing of LAI was first tested with TM because the 30m pixel size represented an area small enough to be directly measured on the ground. However, tests at AVHRR scale 1.1-km soon followed, because this scale is more realistic for global application. One major advance for AVHRR scale LAI validation has been the development of a portable integrating radiometer that can accurately measure forest LAI over multiple kilometer areas (Pierce and Running 1988). Spanner et al. (1990) used the older method of measuring tree diameter or sapwood basal area and allometric equations to calculate plot LAI on conifer forest sites in Washington, Oregon and Montana. They found the AVHRR NDVI correlated to LAI with a function asymptotic at LAI = 3, $R^2 = 0.76$. In a more theoretical approach, Nemani and Running (1989) used a hydrologic equilibrium theory to estimate LAI of 52 1.1-km conifer stands in Montana, ranging from LAI = 1-5. AVHRR/NDVI correlated with these estimated LAI highly, $R^2 = 0.88$. The relationships between LAI and NDVI for conifer forests exhibited asymptotic nature in agreement with radiative transfer theory, though the point of saturation was well beyond an LAI of 4-5, compared to those derived from 1-D radiative transfer simulations of 2-3. With the onset of 3-D radiative transfer models (Myneni et al.,1992), the focus has changed from homogenous canopies as in the case of crops to one of complex heterogenous canopies that are common in natural landscapes. Using a 3-D model (Myneni et al., 1992, Asrar et al., 1992) concluded that for remote sensing purposes leaf area index is less of an instructive parameter than ground cover, *gc* and clump leaf area index, *lc*. The separation of Canopy LAI (CLAI) into *gc* and *lc* would explain the results from Orgeon study. The strong climatic gradient on the Oregon transect would produce differences in both *lc* and *gc* leading to a strong relation between CLAI and NDVI. NDVI is found to vary monotonically with fraction of vegetation cover for various biome types (Price 1992, Huete et al.,1985, Nemani et al.,1993).

2.2 FPAR

Theoretical studies of canopy radiation penetration theory explore the physics of how light interacts with a plant canopy, in order to better understand remote sensing data (Myneni et al., 1992). These studies concentrate on the fate of incoming radiation, not on the canopy structure per se, and describe their results as intercepted PAR, or FPAR, paying specific attention to spectral differences in radiation absorption and reflection (Goward and Huemmerich 1991). A significant part of the theoretical effort recently has been the unification of theory between description of plant canopies by LAI and by FPAR through the separation of ground cover (gc) and clump leaf area (*lc*) (Asrar et al., 1992; Sellers et al.,1992, Myneni and Williams 1994). Asrar et al., (1992) theoretically showed an important interrelationship amongst leaf area index (LAI), fraction of intercepted photosynthetically active radiation (FPAR) and NDVI that improves the utility of these biophysical variables. They found that under specified canopy reflectance properties (for a given biome), FPAR was linearly related to NDVI, and curvi-linearly related to LAI approaching the asymptote at an LAI of 6 where virtually all incident shortwave radiation is absorbed by the canopy. Further analysis by Myneni et al 1992, Myneni and Williams 1994, showed that the relation between FPAR and NDVI is similar for homogenous 1-D and heterogenous 3-D canopies. This important result indicates that the relationship is independent of the heterogeneity in the pixel, thus scale invariant.

Consequently, given a canopy of known structure (biome type) and light scattering and absorbing properties, any one measure of the canopy can be used interchangeably with the others with some algebraic manipulation of formulae. It must be recognized here that different biomes have radically different canopy structure and reflectance properties so can produce different NDVI while having identical LAI. An NDVI of 0.5 may represent LAI = 3 in a forest but only 2.0 in a grassland. Accurate utilization of the NDVI requires that the biome type be known so that the appropriate NDVI to LAI or FPAR conversion can be made. Further, observational details such as the solar zenith angle, sensor look angle, background (soil) exposure fraction and extent of uncorrected atmospheric interference change the NDVI-LAI-FPAR relationship significantly (Sellers 1985, 1987, Asrar et al.,1992, Myneni and Williams 1994). Background influences from soil, litter and under-story vegetation could significantly affect the extraction of FPAR or LAI from satellite observations (Asrar et al., 1992, Baret and Guyot 1991, Goward and Huemmrich 1991, Nemani et al., 1993).

2.3 INSTRUMENT CHARACTERISTICS

The most important instrument characteristics for these products are the MODIS Reflectances (MR) in the Red and NIR wavelengths. The radiometric and atmospheric corrections to the MR will be crucial. Since this product is derived directly from MRs, the instrument characteristics that drive the quality of the MR will be most significant to deriving LAI or FPAR.

3.0 **ALGORITHM DESCRIPTION**

In this section, we will outline our approach to the estimation of LAI/FPAR, along with a historical perspective on the development of the methods/models used in the algorithm.

3.1 RADIATIVE TRANSFER MODELLING OF BIOMES

Biome Characterization: Although the cause and effect relation between Spectral Vegetation indices (SVI) such as NDVI and LAI/FPAR can be established theoretically (Myneni and Williams 1994,Myneni et al.,1995a, Myneni et al.,1995b), its utility depends foremost on the sensitivity to biome characteristics. For instance, if several biomes have a similar or a nearly similar NDVI-LAI relationship, information on such land covers is redundant for the estimation of LAI. As this is hardly the case across different land covers, we must first stratify the global land covers into biome types that have sufficiently different NDVI-LAI (or FPAR) relations which warrant their use in order to satisfy a given accuracy criterion. This implies that traditional land cover classifications based on botanical, ecological or functional metrics may be unsuitable for LAI/FPAR estimations, because these classifications are not necessarily based on NDVI-LAI/FPAR considerations (Loveland et al 1991, Running et al.,1994, Nemani and Running 1995). For example, biome definitions such as C3 and C4 grasses are not meaningful from a radiative transfer point of view as both canopies have similar structural/optical properties. Therefore, a land cover classification that is compatible with the LAI/FAPAR algorithm must be first developed.

After an extensive literature review of canopy radiative transfer modeling (Myneni et al.,1995b) and leaf optical properties (Jacquemoud and Baret 1990) and previous studies dealing with LAI/FPAR estimation (Price 1992, Baret and Guyot 1991, Asrar et al., 1984, Myneni and Williams 1994, Goward and Huemmerich 1992, Hall et al., 1992, Selllers et al., 1994, Li and Strahler 1992), here we define, for the explicit purpose of LAI/FPAR estimation, global land cover into six classes (Table 1). The fundamental basis for this classification is that the structural attributes of these biomes can be parameterized in terms of variables that many radiative transfer models admit. While this six cover class scheme may seem out-of-the ordinary and/or redundant with other MODIS land cover products, we deem it to be necessary for accurate implementation of our algorithm. Also we believe cover classes defined in various existing classification schemes (Loveland et al., 1991, Strahler et al., 1996, Townshend et al., 1996, Running et al., 1994) could be easily collapsed into six classes. Further discussion on the derivation of these classes and how they fit into the proposed MODIS land cover product is given later in this document. A brief description of each of six classes, in terms of important structural properties, is given below.

<u>Biome 1 : Grasses and Cereal Crops</u> Canopies are vertical and laterally homogeneous, vegetation ground cover is about 1.0, plant height is generally less than a meter, erect leaf inclination, no woody material, minimal leaf clumping and intermediate soil brightness. The one-dimensional (1D) radiative transfer model is invoked in this situation. Leaf clumping is implemented by modifying the projection areas with a clumping factor generally less than 1.

<u>Biome 2 : Shrubs</u> Canopies are laterally heterogeneous, low (0.2) to intermediate (0.6) vegetation ground cover, small leaves, woody material and bright backgrounds. The full three-dimensional (3D) model is invoked. Hot spot, i.e., enhanced brightness about the retro-solar direction due to absence of shadows, is modelled by shadows cast on the ground (no mutual shadowing as ground cover is low). This land cover is typical of semi-arid regions with extreme hot or cold (Tundra/Taiga) temperature regimes and poor soils.

Biome 3 : Broadleaf Crops   Canopies are laterally heterogeneous, large variations in vegetation ground cover from crop planting to maturity (0.1 to 1.0), regular leaf spatial dispersion, photosynthetically active stems, i.e., green stems and dark soil backgrounds. The regular dispersion of leaves (i.e., the positive binomial model) leads to a clumping factor that is generally greater than 1. The green stems are modeled as erect reflecting protrusions with zero transmittance.

Biome 4 : Savanna   Canopies have two distinct vertical layers, an under-story of grass (Biome 1), and an over-story of trees with low ground cover (approx. 0.2), canopy optics and structure are therefore vertically heterogeneous. The full 3D method is required. The interaction coefficients have a strong vertical dependency. Savannas in the tropical and sub-tropical regions are characterized as mixtures of warm grasses and broadleaf trees. In the cooler regimes of the higher latitudes, they are described as mixtures of cool grass and needle trees.

Biome 5 : Broadleaf Forests   These canopies are characterized by vertical and lateral heterogeneity, high ground cover, green under-story, mutual shadowing by crowns, foliage clumping. Trunks and branches are included so that the canopy structure and optical properties differ spatially. Mutual shadowing by crowns is handled by modifying the hot spot formulation.
Therefore, stand density and crown size define this gap parameter. The branches are randomly oriented but tree trunks are modeled as erect structures. Both trunk and branch reflectance are specified from measurements.

Biome 6 : Needle Forests   Needle clumping on shoots, severe shoot clumping in whorls, dark vertical trunks, sparse green under-story and crown mutual shadows characterize these canopies. Needle forests exemplify the most complex case, invoking the full 3D method with all its options. A typical shoot is modeled to handle needle clumping on the shoots. The shoots are then assumed to be clumped in the crown space. Mutual shadowing by crowns is handled by modifying the hot spot formulation. The branches are randomly oriented but the dark tree trunks are modeled as erect structures. Both trunk and branch reflectance are specified from measurements.

3.2 RADIATIVE TRANSFER MODEL

A radiative transfer model capable of simulating radiation scattering and absorption in the six biomes defined above is central to implementing the land cover classification and in estimating LAI/FPAR from reflectance measurements. In this section, our published radiation modeling efforts are summarized and recent modeling activities are described. Our initial efforts were concentrated on horizontally homogeneous, i.e., one-dimensional (1D), canopies with the objective of simulating radiation interactions in broadleaf crops and grasslands. Considerable attention was paid to the derivation of appropriate scattering phase functions and their analytical solutions. The governing transport equations were numerically evaluated by the modified discrete ordinates method. The methods were bench-marked by comparing model results to published solutions (Myneni et al.,1988). The model results were compared to field measurements of soybean and maize reflectance measurements for trends and accuracy (Myneni and Shultis 1988). A finite element method was incorporated into this 1D model to obtain fast and accurate numerical solutions (Myneni et al.,1988). The model was modified to include multiple vertical layers in order to simulate grassland reflectance (Asrar et al.,1989) where the under-story in unburned sites was litter from previous years. The model was also compared to a semi-analytical method and found to be four-digit accurate in most situations (Ganapol and Myneni 1992). The model was numerically inverted with considerable success (Privette et al., 1994) and validated by Privette (1994) with atmospherically corrected AVHRR data over the First International Field Experiment (FIFE) sites in a grassland prairie. The 1D model was coupled to an atmospheric radiation model to simulate top of the atmosphere and canopy surface bi-directional reflectance distributions (Myneni et al.,1993). A formulation of the three-dimensional (3D), i.e., horizontally and vertically heterogeneous, radiative transfer equation, the constituent interaction coefficients and its numerical solution were first reported in Myneni et al.(1990). The method was partially validated with PAR transmission measurements in a cottonwood stand (Myneni 1991). Its application to optical remote sensing of vegetation was illustrated and results on model comparison with reflectance measurements from a hardwood forest were presented (Myneni et al.,1992). The 3D method was also validated extensively against shrub lands reflectance measurements from a shrub land in the African Sahel (Begue and Myneni 1996) and found to reproduce the non-linear canopy-soil interaction in sparse canopies well. The 3D model was also used as a boundary condition in an atmospheric radiative transfer problem to study the adjacency effect (Myneni and Asrar 1991). The model has been used to benchmark several other methods and results on model inter-comparisons with the discrete ordinate model as a reference were presented in Myneni et al. (1995a).

Recent Model Developments: Leaf clumping was included in the formulation of the extinction and the differential scattering coefficients. The concept of particle distribution functions from statistical mechanics was utilized to derive analytical expression for leaf clumping (Myneni and Asrar 1991). A simplified model of leaf clumping based on this theory is now included in our model to simulate clumped, random and regular leaf dispersions in space. Vertical tree trunks and randomly oriented branches are also included in the current version of our model. Radiation interaction coefficients for the ensemble of leaves and trunks/branches are derived as linear mixtures with weighting proportional to their areal fractions. The absence of light transmission in trunks and branches imbues an asymmetry critical to the simulation of surface bi-directional reflectance in forest canopies. The hot spot model of Verstraete et al. (1990) has been implemented in our radiative transfer formulation. This model is perhaps the most realistic of existing models of the hot spot effect and is driven by average gap size between leaves in a canopy. In forest canopies, however, where tree crowns mutually shade one another, crown shadowing has been implemented as the driver of the hot spot effect as opposed to gaps between leaves. The method of calculating mutual shadowing is based on the work of Li and Strahler (1992), and its assimilation into the hot-spot model of Verstraete et al. (1990) is rather ad hoc at the present time (i.e., the gap radius is derived iteratively from the proportions of illuminated and viewed crown and background). The resulting reflectance distributions show deepening of the bowl shape due to mutual shadowing, and are generally in good agreement with published results of Li and Strahler (1992) (their figures 7 to 11). Finally, in the case of needle canopies, geometric models of needle clumping on shoots and shoot clumping in whorls are implemented according to a formulation developed by Oker-Blom et al. (1991). With these developments, the model is seen to be reasonably well capable of simulating radiation scattering and absorption in the six land cover types identified earlier, i.e. grasses/cereal crops, shrubs, broadleaf crops, savannas, broadleaf and needle forests. The model is currently being validated with data from a filed experiment in the Canadian boreal forests (BOREAS) and is being used extensively by the Moderate Resolution Imaging Spectro-Radiometer (MODIS: BRDF, Atmospheric corrections, VI) and Multi-angle Imaging Spectro-Radiometer (MISR: BRDF, FPAR) EOS-AM instrument science teams.

Example Simulations: The hemispherical directional reflectance factors (HDRFs), defined as the ratio of radiance of a vegetated surface to the radiance of a reference (conservative and lambertian) surface under identical conditions of illumination (direct sunlight and diffuse skylight) and viewing, of the six land covers defined earlier were simulated in an effort to determine how the canopy structures affect the angular distribution of radiation emerging from these media. In all cases, canopy leaf area index (over- and under-story) was 2.0, solar zenith angle was 30^{o}, and the fraction of direct in total incident radiation was 0.8. The leaf and stem/trunk optical properties given in Table 2, were used in the simulations. The soil reflectance in the medium brightness class (Table 3) was used to parameterize the lower boundary condition. The fraction of stem, trunk, and branch area indices was varied from 10% (Biome 3) to 15% (Biomes 5 and 6) of the plant leaf area index. Canopy height was varied depending on the Biome (0.8-1.2m in Biome 1, 2 and 3, and 10m in Biomes 4, 5 and 6). The tree crown dimensions were also varied (8x4m in Biome 5 and 7x2m in Biome 6), to approximate wide and narrow crowns characteristic of broadleaf and needle canopies. Under-story leaf area index was set to 0.5 in Biomes 5 and 6. Calculations were performed at both red and near-infrared wavelengths.

The results for the near-infrared waveband are shown in Figs. 1a & b, to document the ability of the model to handle strong multiple scattering typical of vegetated surfaces at this waveband. The angular distribution of HDRFs in the principal plane (i.e., the plane of the sun) shows the typical bowl shape, with backscattering generally greater than forward scattering, and a hot spot about the retro-solar direction. The simulation of Biome 1 invokes the one-dimensional turbid medium approximation of the plant canopy, and shows the characteristic HDRF distribution of vegetation canopies. The inclusion of vertical stems with reflectance similar to leaves and zero transmittance (Biome 3) has the effect of increasing theoptical depth of the medium, i.e., overall reflectance increases because of increased multiple scattering. The hot spot is also broadened, as leaves of broadleaf crops are generally bigger than the thin elongated leaves in grasses and cereal crops (Biome 1). When a sparse over-story of trees (ground cover less than 20%) is introduced above the grass under-story (Biome 4), the HDRFs at oblique views increase greatly because of long path-lengths through the under- and over-story canopy media. The hot spot in this instance is considerably narrow perhaps because the thin elongated leaves of the under-story have smaller gap radii as in the case of Biome 1, but the height of the canopy now includes the over-story, an artifact that needs to be addressed. The effect of horizontally aggregating leaf area to reduce ground cover from 100% (Biome 1) to 50% (Biome 2) is increased backscattering, decreased forward scattering and decreased variation around the retro-solar direction --- effects that are primarily due to increased interaction of the soil surface (note that the soil surface was modeled as a lambertian diffuser in all cases). The inclusion of crown mutual shadowing (Biome 5) results in a deepening of the bowl shape and a broadening of the hot spot as it primarily increases the proportion of sunlit crowns along a given viewing direction. Finally, the inclusion of needle clumping and, trunks and branches darker than the needles, results in a decrease of the overall optical depth of the medium (Biome 6), with HDRFs of considerably lower magnitude.

3.3 LAND COVER CLASSIFICATION

As the earlier discussion indicates, an accurate land cover map is a pre-requisite for choosing the appropriate relation between surface parameters (LAI or FAPR) and satellite derived reflectances. Though it is not our responsibility to produce a deliverable land cover product, here we illustrate one approach for producing the six land cover classes that is consistent with the LAI/FPAR algorithm. This algorithm improves upon earlier methods used in Running et al.(1994) and Nemani and Running (1995).

The derivation of land cover classification is rather straight-forward as shown in Figure 2 and uses only remotely sensed observations of NIR, RED and surface temperatures. Non-vegetated areas (permanent snow, exposed soils, deserts, etc) are first identified. Long-term monthly and yearly NDVI averages and standard deviations are examined to separate vegetated areas from non-vegetated areas. The seasonally averaged NDVI value less than a threshold (0.04 NDVI in the case of AVHRR Pathfinder NDVI data) is the first metric used to identify bare areas. Similarly, vegetated areas are identified by seasonally averaged NDVI values greater than a threshold (0.08 NDVI). Results from the above conditions are illustrated using Pathfinder NDVI over Asia (Figure 3). The distribution of the coeffcient of variation (specifically, its inverse) of the remaining pixels is then examined for bi-modality and a threshold is selected to classify these pixels. While it is easier to identify areas that are definitely bare and those that are definitely vegetated, an element of subjectivity always remains in the classification of the intermediate pixels. Vegetated areas are then divided into tropical, temperate and boreal zones depending upon the duration of the freezing period. Within each of these zones, forests are first separated from non-forests based on the magnitude of NDVI at maximum surface temperature. The forested areas in the temperate and boreal zones can be further separated into leaf and needle forests by magnitude of near-infrared reflectance at maximum NDVI (Fig. 1).

The non-forested areas are classified into savanna, broadleaf crops, shrubs, and grasses/cereals depending on the magnitude of red reflectance at maximum NDVI. The thresholds used in these classification are subjective and are specific to the NDVI data set used for classification. This classification scheme was implemented on the monthly composite 8km AVHRR Pathfinder data (James and Kalluri 1994). The resulting land cover distribution is shown in Figs. 4a & b. The classification for the US was compared with the land cover classification of Loveland et al. (1991) which utilized an extensive amount of ancillary information (Table 4). The results indicate that Biomes 2, 5 and 6 can be identified successfully about 75% of the time. The worst case was broadleaf crops, which was mis-classified 40% of the time as broadleaf forests. The land cover classification presented here has the advantage of being simple, operational and compatible with the radiation model used to derive LAI/FAPAR algorithm. It can be easily extended to higher resolution 1km AVHRR data when these become available. The main disadvantage of this implementation strategy is the validity of the thresholds. Incomplete and/or incorrect atmospheric correction can result in misclassification. The impact of such misclassification on the estimation of LAI and FAPAR needs to be investigated. In addition to thresholds, we are investigating the utility of seasonally integrated greenness and ratio of backward to forward scattering as potential metrics for classification. The latter is especially promising as Multi-angle Imaging Spectro-Radiometer (MISR) data will be available in the EOS era.

Note that there are other land cover products produced by full-time MODIS team efforts (Strahler et al., 1996 and Townshend et al., 1996). The final MODIS land cover product includes many more classes, designed to serve a wide variety of users. However, many of the proposed classes are redundant to our approach. For example, deciduous and evergreen labels are not appropriate from a radiative transfer point of view. We believe our six classes could be easily derived from the list of classes proposed as a part of MODIS land cover product (see Strahler et al., 1996 and Townshend et al., 1996). Lastly, our land cover efforts here were meant only to illustrate the utility of using a consistent logic for deriving LAI/FPAR products. It also helps us to exercise our algorithm during pre-launch time, as illustrated later in this document.

3.4 LAI/FPAR ALGORITHM

The relationship between a spectral vegetation index such as NDVI and surface parameters LAI and FPAR has been extensively studied (reviewed in Myneni et al.,1995a). The theoretical basis of these relations was given earlier. We propose to utilize these relations for the estimation of LAI and FPAR, after assessing their robustness with respect to variations in ancillary parameters of the surface and measurement geometry. Standard canopies of the six land covers described earlier were defined in terms of parameter values considered typical from a remote sensing point of view (Table 5). These canopies will be hereafter referred to as the base cases. The base case of each land cover consisted of 13 canopies of varying leaf area indices (0.1-7.0). In the case of savanna and forest land covers, a range of under-story leaf area index was also considered (0.0-5.0). Spectral reflectance and absorptance at red, near-infrared and PAR wavelength bands were calculated for all the 208 canopies of the six land covers with the radiative transfer model discussed earlier. The resulting NDVI-LAI and NDVI-FPAR relations are shown in Figs. 5a & b.

The relationship between NDVI and LAI is nonlinear and exhibits considerable variation among the biomes. Not surprisingly, the relationships for vertically inhomogeneous land covers such as the savanna and forests are strongly dependent on the under-story leaf area index (Fig. 5a). There is practically no sensitivity in NDVI to over-story LAI in forest canopies with a dense under-story (Nemani et al.,1993, Spanner et al.,1990, Chen and Cihlar 1996). NDVI of leaf canopies such as grasses and crops always tends to be higher than forest canopies with similar LAI, because the tree trunks and branches in the latter tend to decrease near-infrared scattering, and therefore low NDVI values. The effect of leaf clumping can also be seen comparing the NDVI values of needle forest canopies with the broadleaf forest canopies at similar LAI values. The NDVI-FPAR relations are linear in most cases, with the exception of canopies with bright NDVI backgrounds (high under-story LAI) (Fig. 5b). These relationships are similar to those reported in the literature based on field data and model results (Peterson et al.,1987, Asrar et al.,1984, Myneni et al.,1992, Spanner et al.,1990, Hall et al.,1995). However, the sensitivity of these relationships to problem parameters, especially sun and view geometry and background brightness, is the critical issue that determines the utility of these relations.

A sensitivity analysis was performed by changing the base case parameter values of each land cover, one at a time, to the end points of the parameter ranges typically encountered in practice. For instance, the leaf normal orientation of leaf forests in the base case simulation was assumed to be uniform (Table 5). The sensitivity to leaf orientation in this land cover was investigated by changing the leaf normal orientation to planophile (mostly horizontal leaves) and repeating all the calculations that were performed in the base case simulation. Another set of calculations was performed with erectophile leaf normal orientation (mostly erect leaves). In this ashion, the NDVI-LAI and NDVI-FPAR relationships were repeatedly simulated for various scenarios to investigate the sensitivity to ground cover, under-story LAI, leaf normal orientation, woody material fraction, leaf and crown sizes, soil reflectance and solar zenith angle. The sensitivity analysis is similar to that described in greater detail in our previous papers (Myneni et al.,1992, Myneni and Williams 1994). All the data were then regressed to obtain land cover specific NDVI-LAI and NDVI-FPAR relations that were statistically significant.

The changes in NDVI, shown in Table 6, must be seen as typical changes one could encounter when the canopies are green and exhibiting the seasonal maximum NDVI, for typical changes in the radiative transfer model parameters and solar zenith angles. Since the NDVI-FPAR relationship is (near) linear, the error in the estimation of FPAR because of uncertainity in the problem parameters is of the same order of magnitude as that given in Table 6 for NDVI. Large variations in NDVI and FPAR (ca. 0.1) can occur if the ground cover is not precisely known. Similar errors occur for shrubs (Biome 2) if the soil reflectance is incorrectly specified (Table 6). The NDVI-LAI relationship, however, is nonlinear; errors in LAI estimates due to NDVI variations (Table 6) are shown in Table 7.

It appears that in most cases uncertainty in the LAI estimate may be of the order of 0.5 LAI. These estimates are valid for canopies at seasonal maximum greenness. A similar analysis is required for the green-up and senescent phases. Whether or not this is within the tolerable range depends on the application for which such a LAI product is intended.

3.5 LUT IMPLEMENTATION OF LAI/FPAR ALGORITHM

Introduction We propose to develop and implement a look-up table (LUT) based approach that utilizes MODIS and on further development MISR reflectances for the estimation of LAI and FPAR. This strategy has the advantage of exploiting the synergy between MODIS and MISR instruments. We believe an approach based on reflectances is considerably superior in the long run over methods based on Spectral Vegetation indices. SVIs basically collapse information from multiple wavelengths, that could otherwise provide additional information about the surface (Figures 1a and 1b). Given that the MODIS/MISR reflectances are well calibrated and atmospherically corrected, the need for producing an index that minimizes these influences is considerably less. There are, of course, several issues that need to be resolved before the full potential of MODIS/MISR synergy can be realized. In this section, we shall concentrate on outlining the key steps and issues in the design and implementation of the look-up table based algorithm.

Description of the LUT Algorithm : The retrieval of LAI and FPAR by the proposed method involves a search engine that utilizes a pixel-wise compound search key to navigate through a look-up table and matches the spectral and angular set of MODIS/MISR measurements with the modeled entries resident in the look-up table. The values of LAI and FPAR corresponding to the best match are reported along with the closeness of the match. A decision is then made whether to trigger the backup algorithm (described later) or not depending on the closeness of the match as compared to a pre-set limit. This sequence of events is conceptualized in Figures 6. A search key is assembled from measurement geometry and information from ancillary data bases of land cover characteristics, fractional ground cover, background reflectance, etc. The observation time determines pixel location and the sun-view directions, i.e., measurement geometry. The location (latitude-longitude) of the pixel is used to identify the land cover characteristics such as the life-form (grasses, shrublands, etc.), phenological state (green-up, senescense, etc.), leaf orientation, woodyness (stem/trunk and branches), crown size and background type (soil, under-story vegetation, moss, etc.). The fractional ground cover can be estimated with concurrent or most-recent nadir MISR observations; a relationship relating the two has been recently developed (Myneni, Nemani & Running, 1996).

The search key is used by a piece of software called the search engine to navigate to the appropriate area in the look-up table. For instance, if the life-form encoded in the search key is Grasses/Cereal Crops, then further searches are confined only to this part of the LUT. Information on phenology, background and sun-view directions (the two angles of each direction will be discretized; actual angles will be nudged to the closest bin) narrows the search finally to a column of discretized LAI values (Fig. 6). Against each LAI value, are the corresponding model simulated FPAR, red/near-infrared MODIS BRFs and off-nadir red/near-infrared MISR HDRFs. The root mean squared error (RMSE) evaluated as the square root of the mean square of the differences between the modeled and measured reflectances is then evaluated for each discretized LAI value. The LAI and FPAR values corresponding to the minimum of the set of RMSE are the retrieved surface products (Fig. 6). The corresponding RMSE will be translated into an error estimate in units of LAI, which will then be used in a decision whether to trigger the backup algorithm or not.

<u>The Look-up Table</u>: The look-up table generation is essentially a factorial combination modeling activity. A series of discrete input combinations are first established and the radiative transfer model is executed for each input parameter combination. The instrument characteristics such as wavelength bands and response functions are built into the appropriate inputs and the output are also similarly tailored (BRFs in the case of MODIS, HDRFs in the case of MISR). Special attention will be paid to the observation geometries of the instruments. The look-up table production time is dependent on the input/output combinations, but is hardly a critical factor as it is not a run-time operation. This is then the primary advantage of the look-up table based approach, as opposed to model inversion or fitting; the heavy processing load is done off-line, prior to launch. This also allows the important aspect of modularity as the look-up tables can be easily switched (so long as the structure of the tables is similar). The final size of the look-up table may be quite variable depending upon the biome, the number of fields required and the density of modeling intervals used. The trade-offs between desired precision and the required computer resources will ultimately dictate the size of the look-up table. *Please see the section on programming and procedural considerations for further details*.

<u>Merits and Demerits</u>: The advantages of this method are several. The algorithm relies chiefly on the radiative transfer model and is therefore physically-based as opposed to algorithms that depend on empirical observations. The model has been developed over a period of 10 years and has been extensively bench-marked and validated with field data. Both the land cover classification and the LAI/FPAR retrieval are tightly coupled via the radiative transfer model, thereby imbuing the entire algorithm with coherence and robustness that should in principle lead to accurate retrievals of known error estimates. The algorithm utilizes spectral and angular information of the component channels to retrieve surface variables as opposed to methods that use only vegetation indices; the back-up algorithm for instance. Note that vegetation indices, by definition, reduce the information content of the component channels (Myneni, Hall, Sellers & Marshak, 1995b). The variance in the observations due to multiple view and sun angles of the same target is exploited by this algorithm rather than seen as a distortionary ìbidirectionalî effect. The algorithm is simple, easy to implement and fast in execution since the problem of fitting model predictions to observations is reduced to

the search of a table of pre-computed model results, rather than repeatedly executing the comprehensive radiative transfer model. The look-up table is generated off-line and is essentially a static element of the algorithm. That means, the look-up table can be updated with improvements in radiative transfer modeling and the entire archive can be reprocessed with minimum effort. This flexibility is extremely important in the design of an operational algorithm, for all contingencies can never be foreseen.

At least two disadvantages of this algorithm are worth mentioning. First, the algorithm relies heavily on the radiative transfer model, i.e., generally speaking, the algorithm is only as good as the model. Therefore, every effort will be made to make the model as realistic as possible and incorporate sub-models from other sources when appropriate. Our radiative transfer model contains the soil reflection model of Jacquemoud et al. (1992), the hot spot model of Verstraete et al. (1990), crown mutual shadowing according to Nilson and Peterson (1991), coniferous shoot geometry and mutual shadowing according to Oker-Blom et al. (1991), model of leaf optical properties developed by Jacquemoud and Baret (1990) and leaf specular reflection according to Vanderbilt and Grant (1985). Continuous checking and validation will be a top priority . Second, the discretization of LAI, ground cover, and the sun-view angles introduces an error that can be remedied only by making finer and finer discretizations. But, this increases the computational and storage load tremendously. A compromise between discretization error and computer related logistics will be accomplished by trial and error.

<u>Planned Activities</u> : Future work on this segment of the algorithm will be focussed on three aspects. First, it is important to find out which of the several model parameters characterizing the vegetation canopy/soil structure and optics need to be discretized. Some of the model parameters, ground cover for instance, are continuous variables, while other parameters, leaf orientation, are not. A discretization scheme will have to be developed and a detailed sensitivity analysis will need to be performed to answer this question. The concept of signal to noise ratio will be employed in the sensitivity analysis. For example, in the case of LAI estimation, the signal can be defined as the partial derivative $\partial\rho/\partial L$, ρ where is the surface reflectance (HDRF or BRF). The noise with respect to a particular model parameter, *x*, can be defined as $\partial\rho/\partial x$. The signal to noise ratio indicates the ability of LAI retrieval from remote observation, ρ, anywhere in the domain of the variable, *x*. This concept is illustrated in Fig. 7, where the interaction between LAI and soil brightness on canopy HDRF at red wavelength is shown for a grass canopy. Surface reflectance decreases with increasing LAI because leaves are strong absorbers at red (Fig. 7). The signal $\partial\rho/\partial L$ is therefore negative. It is stronger at low LAI values and over bright soils because of the contrast. The noise $\partial\rho/\partial\omega_s$ increases exponentially with soil brightness, especially at low LAI values. As a result, the signal to noise ratio is substantial only for soils of moderate brightness and LAI values (Fig. 7). Therefore, one can conclude that surface reflectance at the red wavelength will be a poor estimator of LAI in sparse canopies over bright soils (both signal and noise are strong) and in dense canopies over dark soils (noise is smaller but so is the signal). In these instances, accurate knowledge of the soil single scattering albedo ω_s is required in order to extract canopy LAI.

Once our sensitivity analysis helps determine which of the model parameters are to be discretized, then the question of discretization interval will be the second aspect of our focussed efforts. The size of the interval sets an upper limit to the accuracy of retrieved LAI/FPAR values. For instance, if LAI is discretized at intervals of 0.25, clearly the algorithm will not be able to differentiate between canopies of LAI differing by less than 0.25 LAI units, even if the remote observations carry the signal. Since the relationship between LAI (and other model parameters) and exiting radiation is nonlinear, discretization of a variable into intervals of constant size is perhaps not the most efficient method. The issue of grid and interval spacing as a function of location in the domain of the variable needs to be investigated. This is a critical issue because it affects the accuracy of retrieval, the size and structure of the look-up table, and ultimately, the time of search and retrieval.

The design of the look-up table and the search engine is the third aspect of proposed activity. This is essentially a software implementation topic, an overview of which appears later in this document (section 4). The critical issues are modularity, efficient coding and fast execution. *For further implementation details, please refer to the FPAR, LAI Algorithm Implementation Plan (AIP) document [http://www.ntsg.umt.edu/modis].*

3.6 EMPIRICAL LAI/FPAR ALGORITHM

Introduction: In order to meet the criterion of minimum accuracy from the LAI/FPAR algorithm, it is essential to have, as a back-up algorithm, a simple and robust method of LAI and FPAR estimation. This back-up algorithm is triggered whenever the main algorithm is unable, for various reasons, to provide LAI/FPAR estimates to a prescribed accuracy. Failure of the main algorithm must therefore be defined in terms of objective criteria; for example, the accuracy of the data product is lower than that of the back-up algorithm. This means that the accuracy of the data products retrieved by both the algorithms must be well established.

We propose a simple biome-specific vegetation index based approach for estimating LAI and FPAR as illustrated in Figures 5a and 5b. A theoretical basis for their derivation and the methods used to produce these relations were given earlier (see sections on Theoretical basis and LAI/FPAR algorithm). Since our interest is in predicting LAI and FPAR, regression relations were fit for all the possible combinations (208 canopies of the six land covers) using the the 3D radiative transfer of Myneni, Nemani & Running (1996). The resulting relationships between nadir NDVI-LAI and nadir NDVI-FPAR are shown in Figures 8a and Figure 8b. These relationships together with the land cover classification (Fig. 4) were used to estimate LAI and FPAR from the AVHRR/Pathfinder data óthe results thus obtained are shown in Figs. 9 & 10. Although the AVHRR Pathfinder data was cloud screened, composited and corrected for rayleigh and ozone effects, more importantly it was not corrected for aerosol scattering and water vapor absorption. Therefore, the dynamic between the end points of the relations (Fig. 8a and 8b) had to be matched by percentile with the observed range in the Pathfinder NDVI data.

Accuracy of the Algorithm: The relationships shown in Figures 8a and 8b together with a spatially appropriate land cover classification can be used as a backup algorithm for instruments on the AM platform. The algorithm is valid for nadir/near-nadir observations (MISR has a nadir viewing camera; composited MODIS observations are likely to be near-nadir, in the forward scattering hemisphere). Although the relationships are statistically significant, the issue of accuracy is important and strongly depends on the quality of satellite data.

Planned Activities: Future work planned on this topic include:

(1) Rederivation of the NDVI-LAI and NDVI-FPAR relationships along the lines described above, but with MODIS and MISR spectral bands and filter functions; the relationships shown in Figs. 5a & b are intended for proof-of-concept only.

(2) Detailed analysis of the error budget and propagation of errors. The error analysis presented in Tables 6 and 7 is when the biomes are at the seasonal maximum greenness stage. A similar analysis is required for the green-up and senescent stages also, to obtain a firm view of the accuracy of the algorithm.

(3) Validation of the relationships using field data from literature, FIFE, HAPEX-SAHEL, OTTER, BOREAS and other field campaigns.

(4) Note that it is not necessary to use NDVI. We plan to investigate the utility of advanced EOS era indices, such as the MODIS vegetation index, in this algorithm (Huette et al. 1994). In all cases, we propose to evaluate the index from atmospherically-corrected surface leaving radiance fields.

The algorithm will be used to process a 15 year AVHRR pathfinder data set to assess its robustness, reliability and accuracy (Figures 9a,b and 10a,b).

3.7 ANCILLARY DATA ISSUES

As illustrated in the sensitivity analysis (see section on Main algorithm), accurate characterization of LAI/FPAR depends on how well the surface is characterized in terms of land cover (optical properties, accurate representation of canopy structure etc.), background (soil reflectance), ground cover and phenological state of vegetation. Here we briefly describe our methodology for compiling these parameters globally.

Leaf Optical Properties An extensive database of leaf level optical properties has been assembled. Over 200 leaf spectra have been gathered for various vegetation types and used to produce representative spectral responses for our six vegetation types. Leaf spectra have been convolved using AVHRR channel 1 and 2 wavelength responses as shown in Table 2. We are in the process of collecting additional spectra and producing MODIS/MISR band responses.

Ground Cover and Phenology   Fraction of ground covered by vegetation in a pixel is one of the most important parameters for retrieving LAI/FPAR. Work is in progress on two parallel methods for deriving this parameter. 1) Use 250m pixel data to quantify fraction green area in a 1km pixel in the MODIS era. We are testing this method with 8km Pathfinder data, where we use 1km global AVHRR data to quantify the green fraction in each of 8km Pathfinder pixels. 2) To use MISR multi-angle data to quantify the green fraction in each 1km pixel (Myneni, Nemani and Running 1996).

Phenological State of Vegetation   The phenological state of vegetation (green-up and senescence) also has significant impact on LAI/FPAR retrievals from our algorithm. Identification of green-up and senescent phases of vegetation will be accomplished using historical data from the Pathfinder dataset. The historical data will help us define probable dates of green-up and senescent phases over various parts of the globe.

Background spectral properties   Accurate characterization of background (soil) reflectance properties is critical to the successful retrieval of both LAI and FPAR, especially in the case of sparse canopies such as grass, shrubs and crops. Here we outline an approach that we will implement to produce soil background properties. A number of ground based soil spectra were collected from Dr. Bernard Pinty, Dr. Alfredo Huette and Dr. F. Baret. The spectra were first classified into bright, medium and dark (Baret et al 1993). For RED and NIR wavelength bands of AVHRR, we computed the mean and SD to obtain a general idea of soil reflectances as viewed by AVHRR sensor. The probability of a sensor viewing soils is greatest when NDVI is at its lowest value. Using NASA Pathfinder data, we extracted RED and NIR reflectances for each pixel during the composite period with lowest NDVI. Then we generated frequency distributions of RED reflectances for each land cover type (except forests). The frequency distribution curve was divided into dark, medium and bright guided by the ground based spectra. Results are summerized in Table 3, a map of the soil background classification is shown in Figure 11. A global soil line similar to the one reported in Baret et al. (1993) was obtained using AVHRR data (NIR=1.65 * RED - 5.89, R2=0.91). Shrubs and barren areas deviated considerably from this relation (NIR=1.84*RED - 11.39, R2=0.89).

3.8 VALIDATION

Our goal is to derive LAI and FPAR from atmospherically corrected MODIS/MISR surface reflectance data with a minimum accuracy of 0.5 LAI and 0.1 FPAR. According to our proposal, a radiative transfer model plays a central in the algorithm development; therefore, its validation is of paramount importance. In addition, both the back-up and the main algorithms for LAI/FPAR extraction depend on the land cover. Thus, not only should the derived land cover classification be validated for its accuracy of life-form representation, but the consequences of mis-classification on LAI and FPAR should be investigated as well. Some of these details of the plans for validating these products are given below. For more details on MODLAND wide validation plans, see http://eospso.gsfc.nasa.gov/validation/ docs.html.

R.T. Model Validation The model has been evaluated for its performance in the case of grasses, crops, shrubs and leaf forests (Figures 12 & 13). Currently, we are evaluating the model for needle forests with the data from the BOREAS project. The model still needs to be validated for the savanna biome, which we hope to do in the context of the Amazonian experiment. We also intend to validate the model with the data sets currently available, as described below. Most of these validation activities are focused on the ability of the model to simulate the angular distribution of canopy reflectance and its radiation absorption

Land Cover Validation An evaluation of the land cover classification will be done primarily in the context of IGBP-DIS activity, which is now focussed on the derivation of a global 1 km land cover classification. Such a classification for the continental US is available at the present time (Loveland et al., 1991). In addition to comparisons with existing and soon to be available classifications, we plan on utilizing a network of sites currently being planned by the MODIS LAND team for evaluation. These plans are not yet finalized and we intend to participate in these activities (The Earth Observer, Vol. 7, No. 4, 1995). The effect of mis-classification on the accuracy of derived LAI and FPAR can be studied theoretically. For example, using the relations shown in Figure 8a for NDVI-LAI, we observe large errors between classes shrubs & confiers and the others, and secondly, that a mis-classification among Grass, Savanna, Broadleaf crops and Broadleaf forests would not produce large errors in LAI over much of the NDVI range.

FPAR LAI/Validation The direct measurement of LAI is simple conceptually, all leaves are harvested, dried and weighed. However, over large areas, and for vegetation like forests, these brute force methods are unreasonable and destructive. Various new instruments have been developed to estimate LAI with portable radiometers from principles of light penetration through canopies (Pierce and Running 1988). However, these measurements most directly validate FPAR, they measure the fraction of PAR that is transmitted through a canopy. Only by inverting canopy radiation penetration models, like Beers law, with assumed extinction coefficients, can LAI be measured.

The accuracy of the algorithms can be stated only through an extensive validation of the LAI/FPAR products. Towards this goal, we propose to develop a 15 year prototype product data set using the AVHRR pathfinder data. The derived products will be compared with most available ground measurements of LAI and FPAR (see below). In addition, the MODIS team is developing a network of terrestrial monitoring sites for the validation of these products (The Earth Observer, Vol. 7, No. 4, 1995). The 17 sites in the US NSF Long Term Ecological Research network will be among these sites providing ground measurements of LAI and FPAR. The IGBP is also planning on a Global Terrestrial Observation Network of sites, some of which may provide LAI/FPAR data. In addition, data from the SCAR campaigns of the MODIS Airborne Simulator can be used in conjunction with ground truth data to validate the algorithm. To do this, we intend to participate in the design and planning of future MAS/SCAR campaigns. These validation activities are foreseen to start from the execution phase and continue beyond the launch of the instrument.

Data Sets for Validation: Several data sets of LAI, FPAR and surface reflectance across a wide range of vegetation types are currently available for validation purposes. They range from data pooled from various investigators funded by the Remote Sensing Science Program of NASA (Walthall et al., 1993) to concentrated field research campaigns such as the grassland study FIFE (Sellers et al., 1988), semi-arid shrublands study HAPEX-SAHEL (Goutorbe et al., 1994), Oregon transect ecosystem study OTTER (Waring and Peterson, 1994), the MARICOPA experiments in cotton canopies near Phoenix, Arizona (Huete et al., 1994) and the boreal forest ecosystem study BOREAS (Sellers et al., 1995). In addition, a large scale study with ecosystem and remote sensing components is being planned for the Amazonian forest and savannas. These studies, together with incidental studies reported in the literature on this topic offer an extensive data base for the validation of our radiative transfer model and the extracted LAI/FPAR data products. We shall draw upon these resources for our validation activities, and also plan on participating in any new studies such as the ones planned by the MODIS Land team towards achieving the stated accuracy requirements for the data products. Below is a brief summary of our current validation activity over conifer canopies.

Previous studies (Peterson and Running 1989) compiled a large number of ground based LAI observations over conifer forests. This dataset provided us with an opportunity to test our model simulations. Leaf area index measurements of conifer forests in Northwestern United States described in Peterson and Running (1989) and Spanner et al. (1990) were used to validate the improved radiative transfer model. LAI was estimated from allometric relations in 73 plots (0.1 acre) at 30 locations in Montana, 16 in Oregon and 27 in California. The vegetation at these sites included many types of conifer stands (pines, spruces, juniper, etc). In order to reduce variance in LAI estimate at the Thematic Mapper scale, the plot level LAI estimates were aggregated to represent variations between vegetation zones controlled mainly by climate (Peterson and Running 1989). LAI estimates for the resulting vegetation zones (9 in Montana, 6 in Oregon, 3 in California) were used to compare with TM derived radiances. Landsat/Thematic Mapper data were acquired for the three regions during the summer of 1984. After locating the plots on imagery, data from near-infrared red (NIR) and Red channels were extracted and converted to radiances adjusted for terrain and partial atmospheric effects (Spanner et al.,1990). Simple Ratio (NIR/Red) for each of the 73 plots was calculated and then aggregated to represent the vegetation zones similar to LAI estimates. Red and NIR reflectances were simulated using the 3D radiative transfer model recently modified for needle canopies as described above. A dark soil background and 75 ground cover were assumed in all the simulations. By changing tree LAI from 1 to 6 (canopy LAI from 0.75 to 4.5), Red and NIR reflectances were simulated to evaluate the Simple Ratio (SR). A highly significant linear relationship was found between canopy LAI and SR ($SR=3.16\ LAI+4.4$, $r^2 = 0.9$). The relations between LAI and observed / simulated Simple Ratios are shown in Fig.14. The modeled relation is very similar to that observed, thus indicating the ability of the model to reproduce radiative interactions in conifer stands in both these wavebands (Chen and Cihlar 1996). However, the modeled and observed magnitudes of the Simple Ratio are not comparable, mostly due of atmospheric effects. The primary difference between the two seems to be a difference in offset, rather than the slope.

3.9 VARIANCE, UNCERTAINTY ESTIMATES

The global range of vegetation LAI is 0 in un-vegetated areas to a maximum of 9 in dense evergreen forests. The normal range for global vegetation is around 1-6. FPAR ranges from 0 for un-vegetated areas, to 0.98 for dense forests. Huete et al (1993) reported that with proper corrections for atmosphere and soil, it is possible to derive green cover estimates to within 10% using a single spectral vegetation index. From our theoretical simulations, we believe at seasonal maximum greenness errors in FPAR would be less than 10%, while for LAI the errors would be on the order 0.5 units. For a detailed discussion on the error analysis, please see section on the Main algorithm. However, these computations would not apply at other stages of plant growth. Several uncertainties exist in deriving LAI/FPAR products. For example, accurate land cover definition is mandatory for deriving consistent LAI/FPAR products. Similarly, errors in atmospheric corrections to the reflectances can have significant impact, as those from ancillary datasets. The quality of ancillary data (phenology, ground cover and background) could be substantially improved during post-launch phase of product generation. Past experience and our simulations show that FPAR could be quantified reasonably accurately under a variety of conditions, however estimating LAI, especially for dense canopies could be prone to errors. However, at an LAI of 4-5 most of the incident PAR is absorbed, additional LAI contributes little to the transpiration or photosynthesis.

3.10 PRACTICAL CONSIDERATIONS

All pixels defined as non-vegetated (water, snow, ice, rock) in the initial MODIS masking are skipped, as is all night-pass data.

4.0 **PROGRAMMING AND PROCEDURAL CONSIDERATIONS**

Development of the FPAR~LAI data produ ct is described here as a three phase process. Phase I entails data acquisition and development of critical ancillary input data sets, Phase II includes generation and verification of the static lookup table (LUT), and Phase III covers the development of the LUT client software. The LUT client software itself consists of two software components. The first is the main algorithm program (*fparlai*), run once daily, and the second is a temporal compositing program (*laicomp*), run at the end of each composite period. The compositing routine reduces a set of up to (8) qualifying intermediate daily products into the official composite period FPAR and LAI image products. There is currently also a pre-processor software component, *laifp3*, required to spatially aggregate the original 250m MODIS visible and NIR reflectances to 1 KM, but this will be eliminated when we move to the MOD43 product as a direct source for 1KM surface reflectance inputs as discussed below. Lastly, since the composite period FPAR, LAI products are generated on gridded

MODIS tiles, some of these final outputs will require another spatial re- gridding step to translate them to a coarse geographic grid, as required by the climate modeling community.

FPAR-LAI LUT generation and the development of a biophysical land cover classification tailored for use by the LUT client software are both performed at the Univ. Montana SCF as a pre-EOSDIS activity. Since the LUT client software represents the sole interface to the FPAR LUT, the EOSDIS PGS will be responsible only for executing these client software components. Interested readers may refer to the FPAR-LAI Algorithm Implementation Plan (AIP) for additional technical documentation on our algorithm design and implementation.

4.1 LUT DEVELOPMENT

FPAR~LAI LUT generation activity is defined here as a factorial combination modeling exercise. A series of discrete input combinations (intervals) are first established, matching the distribution of values in spatial data layers to be used by the LUT client software. The 3D Myneni, Nemani and Running (1996) radiative transfer (R-T) model is run for each input/geometry combination, producing a total of 65 LUT entries per run (since each run is parameterized for 8x8 directions, plus 1 for nadir). The exact parameterization intervals used to build a particular LUT are intimately tied to the properties of the spatially (and temporally) dependent layers to be used by the LUT client software. For each compound search key constructed at run time by the LUT client software, a match should always be found. This reliability is ensured from the way the real time (e.g. PGS context) inputs are structured, where continuous variables such as sensor and solar angles have already been nudged to their closest equivalent in the LUT, and discrete ancillary inputs have been designed to exactly match the combinations present in the LUT.

Once the density (e.g. number of input factor intervals) for each driving LUT variable is established, inputs are prepared and a modified version of the Myneni 3D R-T model is run for each combination of inputs identified. The time required to compute a full LUT is a direct function of how many discrete intervals are modeled. Generating trial LUTs thus far have taken approximately 192 computer hours using medium performance IBM RS/6000 RISC workstations. The time to generate a full six biome LUT is expected to improve with better compute servers. We currently have one RS/6000 8-way SMP compute server and are also investigating a DEC Alpha 4100 SMP computer for use in LUT generation. These components are part of the MODIS Compute Ring complex at the University of Montana SCF, which also includes an evolving RAID complex and automated, high capacity tape robot. The primary rationale for adoption the LUT approach is that the heavy processing load required for LUT generation is off-loaded from the EOSDIS PGS as a pre-launch SCF activity. This reduces the routine EOSDIS PGS compute effort to a table lookup operation characterized by an (O log n) worst case performance bound, using a binary search on the sorted table. In the PGS context, the resulting lookup operations are dominated by integer rather than floating point operations; the MFLOPS metric (which accentuates floating point loads) used to characterize MODIS data products may be somewhat less useful in characterizing the performance of this approach.

The final size of the LUT is variable, as it is dependent on both the number of fields required and the density of the modeling intervals used. Refer to Table 9 for the encoding used in the LUT variables. A number of sensitivity analyses are being performed to ascertain a reasonable interval density. The tradeoffs made between desired precision and the amount of computer resources required to implement it will ultimately dictate the sizes of the operational LUT. The full default LUT is generated one *partition* at a time, with a *partition* defined as one combination of wavelength, phenological state, and under-story variable. The default LUT interval density defines 12 such partitions for each biome. One partition of R-T 3D model outputs represents 1950*65= 126,750 records, since 65 sensor geometries are modeled per combination of solar geometry. As an example, GRASS biome R-T model runs are organized into 12 biophysical partitions, each producing 1950 distinct FPAR, LAI_{pix} outputs, for a total of 126,750 BRF outputs. The raw outputs from all 12 partitions when combined into the formal LUT result in 760,500 records per biome, or 4,563,000 records for all six biomes. At 14 bytes per LUT record, this equals 63,882,000 bytes (ca 64MB) for the full (6) biome LUT. These LUT sizes are considered within the bounds reasonably handled on a workstation possessing 128 MB of core memory. Note that in future LUT versions, not all biomes will have the same LUT density, resulting in a LUT that will be somewhat smaller than the original in which all biomes possessed the same interval density.

<u>LUT Access Method:</u> We have considered a number of alternative LUT access schemes, including ISAM based indexing and hierarchical data tree forms. We believe that given the modest size of the final LUT (i.e. 64MB) the marginal performance benefit offered by increasingly more complex designs does not justify their complexity or additional size. We have thus adopted a simple fixed record, binary file organization for the LUT itself. (See Table 8 for LUT record layout). The LUT client software uses a basic binary search algorithm equally applicable to either a sparse and non-sparse key ordering design. One of the few structural requirements posed by our implementation is that the LUT records must be sorted in ascending nested-key order. Since the full LUT contains the contiguous data associated with the (6) separate biomes, a biome key is first used to effect a direct offset jump to the start of the appropriate segment (the 760,500 records for the selected biome) within the LUT. The binary search for a given pixels key is thus limited to just the (760,500) LUT records applicable to the pixels biome, further narrowing the search space.

By default, the LUT is structured as a full (non-sparse) rectangular, bianry flat file in which records for all input product-combinations are present. Should it become necessary for efficient storage, a vertically sparse rectangular layout could readily be adopted. In a sparse design, just the records for the biophysically unique combinations are stored. Each of these storage schemes have implications to the access method used. For non-sparse LUT designs, an even more direct and efficient access methodó a simple serialization function ñ may also be used. This type of function accepts a set of compound key values as inputs, and returns a single direct linear (1D) offset address into the LUT.

The binary search method we use now allows us to use the efficient key comparison and table search functions (e.g. bsearch() and memcmp() functions) found in the standard ANSI C X3J11 and POSIX 1.x libraries. The standard MFLOPS computational metric is a somewhat inappropriate measure for expressing the relative search effort (or net time) required to produce a given FPAR or LAI value. An in-memory binary search algorithm typically contains only integer addition, subtraction, comparison, and assignment statements. This algorithm thus requires only integer class machine operations. In the worst case, the binary search algorithm on properly sorted data never uses more than log(N+1) comparisons for either a successful or unsuccessful search. For a given biome, assuming an implementation relying on a ìworst caseî probe of the LUT table with 760,500 sorted entries, at most 7 comparisons would be required per search to locate a match.

Since the FPAR, LAI lookup table must match the interval scheme used in the phenology, percent ground cover, and understory class ancillary data layers, a new LUT must be generated if the coding scheme or intervals for any of these is revised. As long as the coding scheme or intervals do not change, the pixel values of these ancillary layers may change without a corresponding update of the LUT. In practice, advances in our knowledge based on newer R-T model generations may result in a new LUT when warrented.

4.2 LUT PERFORMANCE AND EFFICIENCY

We assume the execution environment for the MOD15 PGS will offer sufficient memory to essentially store the full LUT in core memory. In recent benchmark tests, we ran our algorithm against a NASA AVHRR Pathfinder (8KM) global data set, with images of 5004 samples and 2168 rows. The test workstation, an IBM RS/6000 Model 59H rated at 264 MFLOPS (peak), contained 256MB of core memory. The input data consisted of 10,848,672 pixels/layer, of which 2,042,489 were classified to one of the six land biomes. Wall clock elapsed time for this informal benchmark was 781 seconds, which of course included all initialization and task I/O. Processing the 2,042,489 LUT pixels required 781 seconds, so we have a net throughput performance of 2615 pixels/second, using the LUT. A similar test run on a IBM Model 41T took 1112 seconds, for a rate of 1836 pixels/second. We therefore feel that LUT access performance per se does not represent an efficiency bottleneck relative to other load components (CPU and I/O). We do note that the effectiveness of the overall LUT approach assumes that sufficient core memory in the execution environment is available to store the fully table, with no significant page faulting (swapping) by the operating systemís virtual memory manager (VMM). This critical locality of reference issue is addressed in the way the LUT itself is structured, where the biome classification serves (the primary key determinant) to group all possible LUT records for a given pixelís probe into a physically contiguous sequence.

Although the approach we use does represent a model inversion scheme, we have considered the natural alternative of invoking the complex Myneni R-T model logic for each pixel processed in real time. The main problem with any real time R-T model approach is relatively large amount of time it requires to compute the FPAR and LAI estimate for a given pixel. We observe the following approximate times, which are biome dependent. For grass biome runs, which represent the simplest canopy, the R-T model runs on average 50 seconds, on our IBM RS/6000 Model 59H workstation, rated at 264 peak MFLOPS. At the other extreme, forest types require ca 180 seconds per run. A run time for a hypothetical ìaverageî biome would approach 90 seconds per run; we feel this is unacceptable performance when we consider the need to process ca 145M pixels per daily execution, even on the more sophisticated DAAC hardware.

4.3 FPAR, LAI ALGORITHM SEQUENCE

Prior to running the main FPAR,LAI algorithm (e.g. the LUT client), the MODIS reflectances for the 250m visible and NIR channels must be spatially aggregated to 1KM tile grid cells. The pre-launch method used a separate pre-processor program (*laifp3*) to read the 250m bands from MOD09 surface reflectance product, and aggregate these to intermediate, 1KM reflectance channels. For the at-launch scenario (V2 and beyond), we intend to use pre-computed 1 KM visible and near infrared, atmospherically corrected surface reflectances available from the MOD43 BDRF database product; this will eliminate the need for the separate *laifp3* pre-processor step. Each input image is projected on the MODIS Land L2G two dimensional integerized, sinusoidal grid and stored in one or more HDF v.4.0 binary files in tile, not swath format. The current MODIS tile size is 1200 x 1200 pixels. To model a full global land coverage, a set of approximately 338 tiles must be processed per day.

4.4 LUT CLIENT SOFTWARE

The LUT client software (***fparlai***) executes daily on a set of co-registered, gridded 1KM reflectance and ancillary input tiles. Stepping through each pixel in row major order, the client software constructs a compound search key from the Control and Surface Parameterization variables listed in Table 8 and performs a binary search using the LUT. The FPAR and LAI values matched for the search key (one per pixel) are then returned, and a root mean square error estimate is calculated by comparing the LUT reflectance string to the MODIS reflectance string. This RMSE is used to identify the best LUT record match from a set of 10 candidates, differing by pixel LAI from the R-T model. Once identified, if the quality of the match meets a user defined threshold, the estimated FPAR and LAI thus calculated are posted to the daily intermediate output tile. If the quality of the match is lower than the set threshold, the FPAR and LAI parameters are estimated using the back up algorithm ñ a family of biome driven polynomial whose independent variable is an NDVI (pre-launch), or MODIS MVI at launch.

Composite periods for Level 4 MODIS Land products are defined as contiguous 8 day sequences. As a given composite period boundary is encountered, the final LUT software component, ***laicomp***, is executed to produce the formal, temporally composited FPAR, LAI product, MODI15. A simple temporal compositing logic is currently employed, where *k* days (2 <= *k* <= 8) of FPAR estimates are compared for each pixel, with the highest valued estimate chosen to represent the pixel for the composite period. The final LAI is chosen to follow the FPAR, since these are related.

4.5 QUALITY CONTROLS AND DIAGNOSTICS

A pixel wise Q/A metric for LAI (and indirectly, for the derived FPAR) may be performed once per LUT lookup by the client software. This is done by comparing the simulated BRF reflectances derived from an R-T model run with the equivalent MODIS derived reflectances, obtaining a sum of squares error metric (e.g. root mean squared error, RMSE, in the variables native units) associated with a given LAI value matched. The RMSE metrics are defined within the real-time, (pixel and time-wise) client process, and so are not stored in the LUT itself but are generated a co-product of a single LUT access by the LUT client software. The RMSE statistic is calculated as:

$$rmse = \sqrt{\sum \left(O_i - P_i\right)^2 / n}$$

where O_i is defined as the ith observed (MODIS) reflectance value {i=1...2} for a given pixel, P_i is defined as the ith (predicted) value for a given pixel, and N is the total number of reflectance channels evaluated (we define 2 for AVHRR pre-launch runs, and 2 -- the MODIS 250m VIS, NIR channels ñ at-launch. This RMSE quality metric relates predominately to the FPAR element and not directly to the LAI_{pix} output parameter. Since the relationship between FPAR and LAI_{pix} is non-linear, we assume a non-linear relationship between the quality value for FPAR and the derivable quality metric for LAI_{pix}. A second order metrics model (with the FPAR error metric as the sole independent variable) is then be applied to estimate the separate ìerrorî associated with the LAI (pixel) output. In addition, the client software observes these basic value range constraints: 1. No calculated LAI_{pix} should exceed range of 0...10 inclusive. 2. No calculated FPAR should exceed the range of {0.0...1.0} inclusive. Interested readers should refer to the University of Montana SCF Q/A Plan for further details on parameter encoding and the Q/A processing sequence.

4.6 EXCEPTION HANDLING

Exceptions are handled on a pixel wise basis within the algorithm. The error classes adopted in this algorithm are: {fatal, serious, warning, and advisory}. In most cases, fatal errors result in termination of the processing of the current tile, assignment of output pixels with Q/A flags, with diagnostic output sent to appropriate log files. Non-fatal errors result in diagnostics sent to log files, Q/A flag assignment. Refer to the University of Montana SCF Q/A plan for additional details on exception handling, coding of various error classes, and quality assurance flags.

4.7 DATA DEPENDENCIES

Both FPAR and LAI algorithms require a Land cover type, 1KM gridded, atmospherically corrected MODIS reflectances and a series of spatially defined ancillary information (phenological state, ground cover percent and understory class/soil background). Note that although we ultimately require a six biome land classification, finer grain land cover classifications may be used equally well as long as a suitable mapping of land types can be made to one of our six broader classes.

4.8 OUTPUT PRODUCT

The FPAR, LAI product consists of a set of 1KM gridded MODIS tiles which together comprise a global extent. Currently, tiles are defined as 1200 by 1200 pixels, where each pixel represents a 1KM square land area. The FPAR and LAI outputs are stored in separate 8-bit data planes, composited on an 8 day basis, in NCSA HDF v.4.x archive volumes. Refer to the MOD15 Interface Control Document (ICD) for further details and specifications on the FPAR, LAI output product.

4.9 CONSTRAINTS, LIMITATIONS, AND ASSUMPTIONS

As the new MR products evolve after launch, both LAI and FPAR algorithms will need to be redefined with new MRs. Our initial (pre-launch) algorithms are based on AVHRR/NDVI data. We expect after-launch improvements in both the Land cover product and MR resulting from using directional MISR data. These improvements will also improve the LAI and FPAR accuracy in ways that we cannot yet predict. We assume the MRs would be corrected for atmospheric effects. While it is easier to estimate fraction of canopy cover or FPAR for pure canopies, it is a major problem for mixed canopies, This problem is particularly severe in conifer canopies with broad-leaf under-story vegetation (Spanner et al., 1990, Nemani et al.,1993). Strong differences in leaf optical properties between the over-story conifer and the under-story broadleaf canopies make the interpretation of VIs difficult. We will expand our modeling and production of LAI/FPAR products for mixed canopies during post-launch period.

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REFERENCES

Asrar G., Fuchs M, Kanemasu ET, J.L. Hatfield. (1984). Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. *Agronomy Journal* 76: 300-306.

Asrar, G. and D. J. Dokken, Eds., (1993). EOS Reference Handbook. NASA, Washington, DC.

Asrar, G., Myneni, R. B., Li, Y., and E. T. Kanemasu. (1989). Measuring and Modeling Spectral Characteristics of a Tallgrass Prairie. *Remote Sens. Environ.*, 27: 143-155.

Asrar, G., R.B. Myneni and B.J. Choudhury. (1992). Spatial heterogeneity in vegetation canopies and remote sensing of absorbed photosynthetically active radiation: A modeling study. *Remote Sens. Environ.,* 41: 85-103.

Baret, F., and G. Guyot. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sens. Environ.*, 35: 161-173.

Baret, F., S. Jacquemoud and J.F. Hanoco. (1993). The soil line concept in remote sensing. *Remote Sens. Rev.*, 7: 65-82.

Begue, A. and R.B. Myneni. (1996). Relationships between NOAA-AVHRR vegetation indices and daily FAPAR established for sahelian vegetation canopies. *J. Geophys. Res.*, 101: 21275-21283.

Chen, J., and J. Cihlar. (1996). Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sens. Environ.*, 55: 153-162.

Clark, et al. (1993). Digital spectral library, USGS, Reston, VA. Http://www.usgs.gov/reports/open_file_reports/93-592/title_html.

Curran P.J. (1983). Multispectral remote sensing for the estimationof green leaf area index. *Phil. Trans. Royal Soc. London* 309: 257-270.

Ganapol, B.D and R. B. Myneni. (1992). The F_N method for the one-angle radiative transfer equation applied to plant canopies. *Remote Sens. Environ.*, 39: 61-74.

Gholz H.L. (1982). Environmental limits on aboveground net primary production, leaf area, and biomass in vegetation zones of the Pacific Northwest. *Ecology* 63: 469-481.

Goel, N.S., and W. Qin. (1994). Influences of canopy architecture on relationships between various vegetation indices and LAI and FPAR: a computer simulation. Remote Sens. Rev., 10: 309-347.

Goutorbe, J.P and others. 1994. HAPEX- Sahel: a large scale study of land surface interactions in the semi-arid tropics. Ann. Geophysicae, 12: 53-64.

Goward, S.M., and K.E. Huemmerich. (1992). Vegetation canopy PAR absorptance and the Normalized Difference Vegetation Index: An assessment using SAIL model. *Remote Sens. Environ.,* 39: 119-140.

Grier, C.C, S.W. Running. (1977). Leaf area of mature northwestern coniferous forests: relation to site water balance. *Ecology* 58: 893-899.

Hall, F.G., K.F. Huemmerich and S.N. Goward. (1990). Use of narrow band spectra to estimate the fraction of absorbed photosynthetically active radiation. *Remote Sens. Environ.*, 32: 47-54.

Hall, F.G., K.F. Huemmerich, D.E. Striebel, S.J. Goetz, J.C. Nickeson and K.D. Woods. (1992). Biophysical, morphological and canopy optical property and productivity data from superior national forest. *NASA Tech. Memo.*, 104558.

Hall, F.G., K.F. Huemmerich, S.J. Goetz, P.J. Sellers and J.C. Nickeson. (1992). Satellite remote sensing of surface energy balance: Success, failures and unresolved issues. *J.Geophys. Res.*, 97(19): 061-090.

Hosgood, B. (1995). LOPEX leaf spectra dataset. JRC, ISPRA, Italy.

Huete, A., and H.Q. Liu. (1994). An error and sensitivity analysis of the atmospheric- and soil correcting variants of the NDVI for the MODIS-EOS. IEEE Trans. *Geosci. Remote Sens.*, 32: 897-904.

Huete, A., C.J. Justice and H. Liu. (1994). Development of vegetation and soil indices for MODIS-EOS. *Remote Sens. Environ.*, 49: 224-234.

Jacquemoud, S. and F. Baret. (1990). PROSPECT: A model of leaf optical properties spectra. *Remote Sens. Environ.*, 34: 75-91.

Jacquemoud, S., F. Baret and J.F. Hanoco. (1992). Modeling spectral and bidirectional soil reflectance. *Remote Sens. Environ.*, 41: 123-132.

James, M.E. and S.N.V. Kalluri. (1994). The Pathfinder AVHRR land data set: An improved coarse-resolution data set for terrestrial monitoring. *Int. J. Remote Sens.*, 15: 3347-3364.

Jarvis, P.G, K.G. McNaughton. (1986). Stomatal control of transpiration. Scaling up from leaf to region. *Advances in Ecological Research* 15: 1-49.

Li, X. and A.H. Strahler. (1992). Geometric-optical bidirectional reflectance modelling of the discrete crown vegetation canopy: Effect of crown shape and mutual shadowing. *IEEE Trans. Geosc. Remote Sens.*, 30: 276-292.

Los, S.O., Justice, C.O., and C. J. Tucker. (1994). A global 1 X 1 NDVI data set for climate studies derived from the GIMMS continental NDVI data, *Int. J. Remote Sens.* 15: 3493-3518.

Loveland, T.R., Merchant, J.W., Ohlen, D.O., and J. F. Brown. (1991). Development of a land cover characteristic data base for the conterminous U.S. *Photgram. Eng. and Remote Sens.*, 57: 1453-1463.

Ludeke, M., A. Janecek and G.H. Kohlmaier. (1991). Modeling the seasonal CO_2 uptake by land vegetation using the global vegetation index. *Tellus*, 43B: 188-196.

Myneni, R. B., Gutschick, V.P., Asrar, G., and E. T. Kanemasu. (1988). Photon transport in vegetation canopies with anisotropic scattering: Parts I through IV. *Agric. For. Meteorol.*, 42: 1-16, 17-40, 87-99, 101-120.

Myneni, R.B., Asrar, G., and S.A.W. Gerstl. (1990). Radiative transfer in three dimensional leaf canopies. *Trans. Theory Stat. Phys.*, 19: 205-250.

Myneni, R.B., Asrar, G., Tanr'e, D., and B.J. Choudhury. (1992). Remote sensing of solar radiation absorbed and reflected by vegetated land surfaces. *IEEE Trans. Geosci. Remote Sens.*, 30: 302-314.

Myneni, R.B. and G. Asrar. (1993). Radiative transfer in three dimensional atmosphere vegetation media. *J. Quant. Spectroscp. Radiat.Transfer* 49: 585-598.

Myneni, R.B., Impens, I., and G. Asrar. (1993). Simulation of space measurements of vegetation canopy bidirectional reflectance factors. *Remote Sens. Rev.*, 7: 19-41.

Myneni, R.B. and D.L. Williams. (1994). On the relationship between FAPAR and NDVI. *Remote Sens. Environ.*, 49: 200-211.

Myneni, R. B., Hall, F.G., Sellers, P. J., and A. L. Marshak. (1995a). The interpretation of spectral vegetation indices. *IEEE Trans. Geosc. Remote Sens.*, 33: 481-486.

Myneni, R.B., Maggion, S., Iaquinta, J., Privette, J. L., Gobron, N., Pinty, B., Verstraete, M.M., Kimes, D.S., and D. L. Williams. (1995b). Optical remote sensing of vegetation: Modelling, caveats and algorithms. *Remote Sens. Environ.*, 51: 169-188.

Myneni, R.B., R.R. Nemani and S.W. Running. 1996. Algorithms for estimating global land cover, LAI and FPAR from radiative transfer models. IEEE Trans. Geosci. Remote Sens., (in review).

Nemani, R.R., and S.W. Running. (1988). Testing a theoretical climate-soil-leaf area hydrologic equilibrium of forests using satellite data and ecosystem simulation. *Agric. For. Meteorol*., 44: 245-260.

Nemani, R.R., L. Pierce, S.W. Running and L. Band. (1993). Forest ecosystem processes at the watershed scale: Sensitivity to remotely sensed leaf area index estimates. *Int. J. Remote Sens., 14: 2519-2534*.

Nemani, R.R., and S.W. Running. 1995. Satellite monitoring of global land cover changes and their impact on climate. Clim. Change, 31: 395-413.

Oker-Blom, P., Lappi, J., and H. Smolander. (1991). Radiation regime and photosynthesis of confierous stands, in Photon Vegetation Interactions, edited by Myneni, R.B., and J. Ross, Springer-Verlag, Berlin, pp501-535.

Peterson, D.L, Spanner M.A, Running S.W, K.B. Teuber. (1987). Relationship of Thematic Mapper Simulator data to leaf area index of temperate coniferous forests. *Remote Sens. Environ.,* 22: 323-341.

Peterson, D.L. and S.W. Running. (1989). Applications in forest science and management, in Theory and Applications of Optical Remote Sensing.

Peterson, D.L., Spanner, M.A., Running, S.W., and L. Band. (1987). Relationship of Thematic Mapper Simulator data to leaf area index. *Remote Sens. Environ.*, 22: 323-341.

Pierce, L.L, S.W. Running. (1988). Rapid estimation of coniferous forest leaf area index using a portable integrating radiometer. *Ecology* 69: 1762-1767.

Price, J.C. (1992). Estimating vegetation amount from visible and near infrared reflectances. *Remote Sens. Environ.,* 41: 29-34.

Privette, J.L. (1994). An efficient strategy for the inversion of bidirectional reflectance models with satelite remote sensing data. PhD Thesis, University of Colorado, Boulder.

Privette, J.L., Myneni, R.B., Emery, W.L., and C.J. Tucker. (1994). Invertibility of a 1D discrete ordinates canopy reflectance model. *Remote Sens. Environ.*, 48: 89-105.

Richardson, A.J., and C.L. Wiegand. (1991). Comparison of two models for simulating the soil-vegetation composite reflectance of a developing cotton canopy. *Int. J. Remote Sens.*, 11: 447-459.

Running, S.W and others. (1994). Terrestrial remote sensing science and algorithms planned for EOS/MODIS. *Int. J. Remote Sens*., 15: 3587-3620.

Sellers P.J. (1987). Canopy reflectance, photosynthesis and transpiration. II The role of biophysics in the linearity of their interdependence. *Remote Sens. Environ.,* 21:143-183.

Sellers, P.J. and D.S. Schimel. (1993). Remote sensing of the land biosphere and biogeochemistry in the eos era: science priorities, methods and implementation ñ EOS land biosphere and biogeochemical cycles panels. *Global and Planetary Change* 7: 279-297.

Sellers, P.J., J.A. Berry, G.J. Collatz, C.B. Field and F.G. Hall. (1992). Canopy reflectance, photosynthesis and transpiration. III. A reanalysis using improved leaf models and new canopy integration scheme. *Remote Sens. Environ.*, 42: 187-216.

Sellers, P.J., Los, S.O., Tucker, C.J., Justice, C.O., Dazlich, D.A., Collatz, C.J., and D.A. Randall. (1994). A 1 X 1 NDVI data set for global climate studies. Part 2: The generation of global fields of terrestrial biophysical parameters from the NDVI. *Int. J. Remote Sens.*, 15: 3519-3545.

Sellers, PJ (1985). Canopy reflectance, photosynthesis and transpiration. *Int. J. Remote Sens.,* 6: 1335-1372.

Sellers. P.J., Mintz, Y., Sud, Y.C., and A. Dalcher. (1986). A simple biosphere model (SiB) for use within general circulation models. *J. Atmos. Sci.* 43: 505-531.

Shultis, J.K. and R. B. Myneni. (1988). Radiative transfer in vegetation canopies with anisotropic scattering. *J. Quant. Spectroscp. Radiat. Transfer*, 39: 115-129.

Spanner, M.A., Pierce, L., Peterson, D.L., and S.W. Running. (1990). Remote sensing of temperate conifer forest leaf area index: Influence of canopy closure, understory vegetation and background reflectance. *Int. J. Remote Sens.*, 11: 95-111.

Spanner, M.A., L. Johnson, J. Miller et al., (1994). Remote sensing of seasonal leaf area index across the Oregon transect. Ecol. Appl., 4: 258-271.

Strahler, A., and others. 1996. ì Modis land cover product î, EOS-MODIS ATBD, NASA/GSFC, Code 900, Greenbelt, MD.

Townshend, J.R.G., and others. 1996. ìLand cover and land cover change algorithmî, EOS-MODIS ATBD, NASA/GSFC, Code 900, Greenbelt, MD.

Verstraete, M.M., Pinty, B., and R.E. Dickinson. (1989). A physical model for predicting bidirectional reflectances over bare soils. *Remote Sens. Environ.*, 27: 273-288.

Waring, R.H., and D.L. Peterson. 1994. Oregon Transect Ecosystem Research (OTTER). Ecol. Appl., 4: 210-211.

Webb W.L., Lauenroth W.K., Szareck S.R., R.S. Kinerson. (1983). Primary production and abiotic controls in forests, grasslands, and desert ecosystems in the United States. *Ecology* 64:134-151

Wiegand C.L., Richardson A.J., E.T. Kanemasu. (1979). Leaf area index estimates for wheat from Landsat and their implications for evapotranspiration and crop modeling. *Agronomy Journal* 71: 336-342.

RESPONSE TO REVIEW OF EOS-AM 1 LAND DATA PRODUCTS FOR ASTER, MISR, and MOSIS

DATA PRODUCT: MOD15 – LAI & FPAR

The following is the response of the ATBD team to reviewer's comments on MODIS land data product MOD15-LAI and FPAR. The panel reviewed both the LAI/FPAR ATBD dated 1994 and Myneni's proposal dated October 1995. This proposal contained the latest information on the MODIS LAI/FPAR algorithm, thus superceding the 1994 ATBD. Therefore, we shall respond principally to the reviewer's comments on Myneni's proposal. This reponse is intended as an appendix to the latest version of the ATBD dated November 1996. One of the principal reccommendation of the 1994 ATBD review was to ask that the then LAI/FPAR group (Running et al.) work with a radiative transfer modeller to strengthen the theoretical aspects of the algorithm. Myneni started working with Running et al. to provide the theoretical support. When NASA issued an announcement of opportunity in October of 1995 soliciting proposals for instrument science team memberships, Myneni's proposal *Radiative transfer based synergistic MODIS/MISR algorithm for the estimation of global LAI and FPAR* was selected in May of 1996, a few weeks before the said EOS-AM 1 Land Data Products review. At the present time, both team members, Running and Myneni, are working together to produce the MODIS LAI and FPAR data product. Therefore, there is only one ATBD (dated November 1996). Below we respond to the reviewer's comments on Myneni's new proposal, which contained the status of the algorithm as of October 1995.

(A) Technical/Scientific Soundness of the Algorithm/Approach Described

What about mixed forest classes, which incidentally constitute > 50% of the BOREAS area.

The LAI/FPAR algorithm requires a global land cover stratification based on vegetation canopy architecture and optics. Thus, the land covers can be defined in terms of parameters that vegetation canopy radiation models admit. At the present time, we are using the following six land cover classes: (1) grasses and cereal crops, (2) shrubs, (3) broadleaf crops, (4) savanna, (5) broadleaf forests and (6) needleleaf forests. The land covers are defined in detail in the ATBD. We are currently able to simulate the BRDFs of these cover types with our radiation model (Fig. 1 in the ATBD). Our radiation model is capable of simulating mixtures of needleleaf and broadleaf forest stands. Therefore, we can include this class into our scheme rather easily. However, we need to know what the component fractions are in the mixture. If the MODIS land cover classification contains the mixture class and the component fractions are known, then we will include this class in our algorithm.

The RT model/LUT approach to estimating LAI and FPAR is critically dependent on the accuracy of the cover type classification; inaccuracies will propagate into the derived values of LAI and FPAR.

The accuracy of MODIS land cover classification is best addressed by the team members responsible for producing the product. How these inaccuracies will affect the LAI/FPAR product is currently being investigated. For instance, if the actual land cover is a broadleaf forest, but is classified as a needleleaf forest, we can investigate the error in LAI/FPAR by comparing the estimates obtained from broadleaf and needleleaf biome-specific NDVI-LAI/FPAR relations (described in the ATBD). The error analysis presented in the ATBD is based on the assumption that the land cover of a pixel is known. Errors in misclassification are not of equal importance. For example, an error between needleleaf and broadleaf forests would be tolerable, while between a grass and a forest would be significant. Numerics on this topic will be presented in detail at the panel review. The inaccuracies in land cover classification, however, must be addressed by team members directly responsible for this product.

The RT model ignores topographic effects.

This issue was discussed during the oral presentations. Apparently, our responses were not satisfactory. Therefore, we present here how topographic effects are addressed in the algorithm. We adopted the formulation developed by Schaaf et al. [IEEE TGARS, Vol. 32, No. 6, 1186-1193, 1994]. Let $[X, Y, Z]$ denote the inertial coordinate system, where the Z axis is directed to the zenith, the X axis pointed eastwards, and the Y axis directed northwards. A direction in this system has a polar angle θ measured from the Z axis and an azimuthal angle ϕ measured counter-clockwise from the X axis. All model calculations, however, are performed in a coordinate system $[X', Y', Z']$ aligned with the slope and aspect. That is, the normal to the slope is Z', the X' axis runs along the surface of the slope in the direction of the aspect, and $Y' = Y$. Thus, the azimuth of the slope is zero. The solar and view angles (θ_o, ϕ_o, θ_v ϕ_v) at the time of MODIS measurement are given in the intertial frame $[X, Y, Z]$. These are converted to the $[X', Y', Z']$ frame according to the relations given in Schaaf et al. (cited above) to obtain the angles (θ'_o, ϕ'_o, θ'_v, ϕ'_v),which are now in the slope aligned frame, i.e., in the coordinate system of the model. The algorithm can now be triggered for the estimation of LAI/FPAR. It is for this reason, that topography is not explicitly included in the model! The implementation of this correction requires (a) a mask to identify which pixels require a topographic correction, and (b) the slope and aspect. Based on Schaaf et al.'s (1994) analysis, we expect to apply this correction in areas where the slope is greater than 15°. This topographic correction scheme has two important assumptions – (a) the pixel is assumed to fill the slope, and (b) all incident radiation is assumed to come from either the sun and the sky, but not from adjacent land areas which can also be in the field of view of an observer located in the $[X', Y', Z']$ frame. This can potentially lead to serious errors in cases of steep slopes and turbid atmospheres when skylight is a larger fraction of the incident radiation field.

It also appears that hotspot effects and mutual shadowing are not appropriately taken into account in the model.

We have several publications detailing our modelling approach and results over the past decade. We are appending here a list of some selected publications as our response to this comment. Whether these and other effects are *appropriately* modelled or not will have to be judged by how well the model simulates observed radiation fields; the ATBD contains several illustrations of the validity of the model and its physics (Figures 12-14 in ATBD).

To further support our claim that important physics, including the hot spot effect and crown mutual shadowing in forest canopies, is included in the model, we refer to Fig. 1, appended here. The figure shows the hemispherical directional reflectance factors (HDRF) of a broadleaf forest in the principal plane, i.e., the plane of the sun; solar zenith angle is 30 degrees in all cases. All model calculations were performed in the near-infrared part of the solar spectrum, where vegetation canopies are highly reflective, i.e., multiple scattering dominates the exiting radiation field. Curve 1 refers to idealizing the broadleaf forest canopy (LAI = 4) as a horizontally homogeneous turbid medium, i.e., vegetation cover equal to 100%. The HDRF distribution is asymmetric about the nadir, with the minima located around 20 degrees view polar angle in the forward scattering hemisphere. Lateral and horizontal heterogeneity is then introduced into this canopy by redistributing the same leaf area as follows. The overstory vegetation cover is reduced to 0.7 and the plant LAI is increased to 5, to result in an overstory canopy LAI of 3.5; the understory is assumed to have vegetation cover of 100% with LAI = 0.5; therefore, the total canopy LAI is 4. The resulting HDRF distribution (curve 2) clearly shows the darkening of the vegetated surface about the nadir directions. This is to be expected for three reasons — (a) leaves are much brighter than the soil at near-infrared wavelengths, (b) decreasing the vegetation cover allows the soil surface to participate in the multiple scattering process and, (c) more soil surface is viewed about nadir directions than along oblique directions. The opposite would be true at red wavelength where the leaves are darker than the soil.

We now introduce finite-sized leaves into this canopy, with unequal leaf hemispherical reflectance and transmittance, and clumping of leaves. Further, we assume that 10% of the overstory plant leaf area is woody material (stems and branches). The woody material has zero transmittance and is generally darker than the leaves at near-infrared wavelengths. Curve 3 is the resulting HDRF distribution in the principal plane. Three points can be made: (a) We can clearly see the hot spot effect because of shadowing between leaves in the crowns. This hot spot effect is considerably narrow because of the size of leaves relative to tree height. (b) The magnitude of HDRFs at all view angles decreases because the woody material is darker than leaves at near-infrared wavelength. (c) Forward scattering is more affected than back scattering because the transmittance of woody material is zero. Crown mutual shadowing is introduced in the model by modifying the formulation for (a) first scattering in the canopy of incident direct solar radiation, i.e., the sunlit fraction of viewed tree crowns and, (b) uncollided radiation intensity exiting the canopy after reflection at the soil surface, i.e.,the sunlit fraction of viewed soil surface. These modifications require evaluation of the bidirectional probability of viewing a sunlit element at different depths in the canopy and at the soil surface, respectively. We adopted the formulation developed by Li et al. (1995) to evaluate these probabilities (IEEE TGARS, Vol. 33, 466-480, No. 2, 1995). Curves 4 and 5 in Fig. 1 show the HDRF distribution in canopies with minimal and maximal crown mutual shadowing. The effect of mutual shadowing is to decrease the viewed shadow area of the scene, thereby increasing the brightness of the scene. The hot spot effect due to crown shadowing can be clearly seen when crown mutual shadowing is minimized (curve 4). Mutual shadowing of tree crowns increases greatly at oblique look angles because only the upper layers of the canopy are seen. And, along oblique backscattering directions, where only the bright elements of tree tops are seen, crown mutual shadowing has the effect of decreasing the contrast due to the crown hot spot effect (curve 5).

Because of the saturation of canopy reflectance with LAI, it is doubtful the hoped for accuracy for LAI will be achieved.

A rigorous theoretical basis for estimating LAI and FPAR from canopy spectral reflectance measurements is given in our recent paper (Myneni et al., IEEE TGARS, Vol. 33, No. 2, 481-486, 1995). A cogent summary of that theoretical development is also given in an appendix to the ATBD. It will be noted from the analysis presented there that exiting radiation fields are always non-linear functions of all important structural and optical properties of the medium, including LAI. The saturation referred to in the reviewers comments is a function of the wavelenth of the radiation field in case. This is precisely the reason why spectral reflectances at different wavelengths are combined to alleviate the saturation problem. For instance, if NDVI is found to saturate with LAI, a simple reformulation of NDVI as the Simple Ratio greatly increases the dynamic range of the relationship (see for instance, Fig. 14 of the ATBD). Of course, there is a limit to the sensitivity of the measurement, and if the measurements carry no signal, then not much can be done. The saturation of the signal depends on the structure of the canopy. In the case of homogeneous canopies like crops, grasses and such, the saturation is at lower values of LAI, typically around 3-4. However, in forest canopies, the measurements retain sensitivity to LAI values as high as 6 to 8, because of varying vegetation cover and leaf clumping.

Further, one will need a very fine grid in LAI space. The algorithm may not be computationally fast enough unless some innovative procedure are developed.

Our response to this comment is addressed in detail in Section 4 of the ATBD, titled "Programming and Procedural Considerations." We are currently working with a look-up-table (LUT) of 64 MB for LAI/FPAR generation. The design allows non-linear spacings to accomodate differential sensitivities of the problem parameters to LAI/FPAR. This LUT size is considered within the bounds reasonably handled on a workstation possessing 128-256 MB of core memory. For instance, a global data set of AVHRR Pathfinder data at 8 km resolution (2,042,489 land pixels) was processed in about 800 to 1100 seconds on standard workstations, including all I/O. That is, a throughput of 1800 to 2600 pixels per second on standard workstations. This performance is achieved because of innovations in LUT design, implementation, LUT access, etc. Therefore, we feel that a LUT approach is the most desirable approach, because of its flexibility, to implement our LAI/FPAR algorithm.

Also, because of the saturation effects, the backup plan will likely fail for high LAI such as those of conifer and broadleaf forests.

We offer Fig. 14 in the ATBD as a response to this comment. It can been that both measurements and our modelling results suggest that simple transforms of canopy spectral reflectances are sensitive to LAIs as high 7 and 8. Also, we refer to our response above regarding the saturation effect, and to the appendix where the theoretical basis for estimating LAI and FPAR is given.

(B) Value of the Data Product to the Land Science Community (N/A)

(C) Soundness of the Validation Strategy

MODIS land science team has a validation strategy, which is discussed in detail in the ATBD. The panel seems concerned about constrained validation, that is, checking for the accuracy of the products in contexts where auxilliary information is known. We have not proposed such an approach, either in the previous ATBD or in the proposal. Therefore, our response is to direct the attention to the validation section in the ATBD and to the MODLAND validation strategy document.

(D) Extent to which 1994 ATBD Review Issues Were Addressed (N/A)

(E) Near-term Recommendations for Improvements to the Data Product

The MODIS and MISR teams are now betting on a single approach to produce this product. As noted above, this approach has shortcomings and we doubt if the claimed accuracy will be achieved. The MODIS and MISR programs should consider fund other approaches starting now (it takes several years to develop and validate the approach).

MODIS is a multi-spectral instrument while MISR is a multi-angle instrument. The MODIS LAI/FPAR algorithm exploits variance in the reflectance measurements to obtain accurate estimates of LAI/FPAR. This synergistic aspect of MODIS algorithm was cited as the key reason for its selection. MISR does not have a LAI product. MISR FPAR product is based on angle-integrated spectral reflectances. Therefore, the approaches are different. It is important to remember that membership on facility instruments such as MODIS is solicited via NASA Research Announcements (NRA) and is open to the entire community. The most recent NRA was in Sep/Oct of 1995. MODIS LAI/FPAR product was solicited, actively competed, and the current synergistic algorithm was selected. We must therefore assume that alternate approaches proposed in response to the NRA were deemed unsatisfactory. Science team membership and algorithm development on PI instruments, such as MISR, are the responsibility of the PI. It is our understanding and conclusion that the various approaches to LAI/FPAR estimation have been assessed through the peer-review process, and the ones most satisfactory have been selected for producing these data products for MODIS and MISR.

The accuracy of this approach is given in the ATBD. For the six biomes, we expect to estimate LAI (FPAR) to within 0.5 (0.1) of their actual value, during times of maximal seasonal greenness. These estimates were arrived at from a sesitivity analysis of the algorithm. MODIS validation strategy will further provide us an opportunity to refine the algorithm. It should be stressed that algorithm development is a continuing activity and the algorithm continues to evolve for the better. There is little heritage in terms of global data product generation operationally, and therefore we are proceeding cautiously in these untested waters.

Work with the recently formed modelling group within BOREAS (chaired by F. Hall and J. Chen) to help evolve a robust approach based on RT modelling.

Both team members, Running and Myneni, are BOREAS investigators and members of this modelling group. Myneni is coordinating the model/algorithm intercomparision effort. As of late October 1996, one only approach other than the MODIS algorithm, was identified. This activity will continue and we will actively seek collaboration with scientists of expertise outside of our strengths.

(E) Long-term Recommendations for Improvements to the Data Product

The MODIS and MISR programs should fund alternate approaches.

We believe that most of the reviewers comments were less than substantive. Therefore, it is somewhat puzzling that they claim *the approach has shortcomings*. It would be very helpful if we knew **substantively** what these shortcomings were. Moreover, the reviewers seem to doubt the accuracy estimates given in the ATBD, although no substantive reasons were given. Therefore, we find their recommendation to fund alternate approaches not warranted given (1) the overall review of the algorithm and, (2) the recent NRA which invited and screened all existing approaches through a peer-review process that is accepted unconditionally by the community.

Articles Describing the Hot Spot Effect in canopy RT models

[1] **Myneni, R.B.**, Maggion, S., Iaquinta, J., Privette, J. L., Gobron, N., Pinty, B., Verstraete, M. M., Kimes, D. S. and Williams, D. L., 1995. Optical remote sensing of vegetation: modelling, caveats and algorithms. *Remote Sens. Environ.*, 51: 169-188.

[2] **Myneni, R.B.** and Asrar, G., 1993. Radiative transfer in three-dimensional atmosphere-vegetation media. *J. Quant. Spectroscp. Radiat. Transfer*, 49: 585-598.

[3] **Myneni, R.B.**, Asrar, G. and Hall, F. G., 1992. A three dimensional radiative transfer method for optical remote sensing of vegetated land surfaces. *Remote Sens. Environ.*, 41: 105-121.

[4] Knyazikhin, Y. V., Marshak, A. L. and **Myneni, R.B.**, 1992. Interaction of photons in a canopy of finite dimensional leaves. *Remote Sens. Environ.*, 39: 61-74.

[5] **Myneni, R.B.** and Asrar, G., 1991. Photon interaction cross sections for aggregations of finite dimensional leaves. *Remote Sens. Environ.*, 37: 219-224.

[6] **Myneni, R.B.** and Ganapol, B. D., 1991. A simplified formulation of photon transport in leaf canopies with finite dimensional scatterers. *J. Quant. Spectroscp. Radiat. Transfer*, 46: 135-140.

[7] **Myneni, R.B.**, Marshak, A.L. and Knyazikhin, Yu., 1991. Transport theory for leaf canopies with finite dimensional scattering centers. *J. Quant. Spectroscp. Radiat. Transfer*, 46: 259-280.

[8] **Myneni, R.B.**, Asrar, G. and Gerstl, S.A.W., 1990. Radiative transfer in three dimensional leaf canopies. *Transport Theory and Statistical Physics*, 19:205-250.

[9] **Myneni, R.B.** and Kanemasu, E.T., 1988. The hot spot of vegetation canopies. *J. Quant. Spectroscp. Radiat. Transfer*, 40:165-168.

[10] **Myneni, R.B.**, Marshak, A. and Knyazihin, M. and Asrar, G., 1991. Discrete Ordinates Method for Photon Transport in Leaf Canopies. In: R.B. Myneni and J. Ross [Eds.], "Photon-Vegetation Interactions: Applications in Optical Remote Sensing and Plant Physiology", Springer-Verlag, pp. 45-109.

THEORETICAL BASIS FOR REMOTE ESTIMATION OF LAI & FPAR

There are many examples in published literature of NDVI-LAI and NDVI-FPAR relations, either based on co-incident measurements or model estimates (reviewed in [1]). While the general body of empirical evidence is convincing, a theoretical basis for the existence of these relations has been published only recently [2]. It was reported that most spectral vegetation indices can be generalized to show a derivative of surface reflectance with respect to wavelength. This derivative is a function of the optical properties of leaves and soil particles. In the case of optically dense vegetation, the spectral derivative, and thus the indices, are indicative of the abundance and activity of the absorbers in the leaves. Therefore, the widely used broad-band red/near-infrared vegetation indices, such as NDVI, are a measure of chlorophyll abundance and energy absorption.

The derivation presented in Myneni et al. [2] is generic, for it includes all published spectral vegetation indices, and the theoretical basis of NDVI-LAI and NDVI-FPAR relations is not readily evident. Therefore, a simple summary is presented here, to establish a theoretical basis for the MODIS LAI/FPAR algorithm.

Vegetation indices typically capture the absorption contrast across the $0.65 - 0.85\mu m$ wavelength interval through combinations of broad-band red and near-infrared reflectance. The most widely used index in the processing of satellite data is the Normalized Difference Vegetation Index (NDVI) defined as $[(\rho_N - \rho_R)/(\rho_N + \rho_R)]$, where ρ_N and ρ_R are spectral bidirectional reflectance factors (ratio of the radiance of a target surface to the radiance of a conservative, lambertian surface) at near-infrared and red wavelengths, respectively. NDVI can be shown to be related to the derivative of surface reflectance with respect to wavelength [2]. To do so, let NDVI $= \Delta V$, $\rho_N = \rho(\lambda + \Delta\lambda)$ and $\rho_R = \rho(\lambda)$. Note that

$$\rho(\lambda + \Delta\lambda) - \rho(\lambda) \;=\; \frac{d\rho}{d\lambda}\,\Delta\lambda \;+\; \Theta[(\Delta\lambda)^2]$$

$$\rho(\lambda + \Delta\lambda) + \rho(\lambda) \;=\; \frac{2}{\Delta\lambda}\int_{\lambda}^{\lambda+\Delta\lambda} d\lambda'\;\rho(\lambda') \;+\; \Theta[(\Delta\lambda)^2]$$

Here $\Theta(\Delta\lambda^2)$ denotes error of order $\Delta\lambda^2$. In the limit $(\Delta\lambda \to 0)$

$$\frac{dV}{d\lambda} \;=\; \frac{d\rho}{d\lambda}\,k$$

where $k = [1/2\rho(\lambda)]$. If one can now show that this spectral derivative is related to LAI and FPAR, the theoretical basis of the VI-LAI/FPAR relations is established.

The spectral derivative can be written as

$$\frac{d\rho}{d\lambda} \;\approx\; \frac{\partial F}{\partial \rho_S}\,\frac{\partial Q}{\partial \omega_S}\,\frac{d\omega_S}{d\lambda} \;+\; \frac{\partial F}{\partial \omega_L}\,\frac{\partial P}{\partial \kappa}\,\frac{d\kappa}{d\lambda} \qquad (1)$$

In the above, ρ_S is soil reflectance, ω_S is soil particulate single scattering albedo, ω_L is leaf albedo and κ is the transmittance of a hypothetical unit layer of leaf interior. The functions F, Q and P describe radiative transfer in a canopy of leaves layered above a soil surface, a semi-infinite medium of soil particles and the interior of a leaf modelled as a pile of transparent plates, respectively. The governing equations of transfer are linear integro-differential equations [1]. The solutions can be expressed formally as a sum of exponential functions, that is, the photon count decays exponentially through successive absorption and scattering events in the media. The partial derivatives ($\partial F/\partial\rho_S$, $\partial F/\partial\omega_L$, $\partial Q/\partial\omega_S$ and $\partial P/\partial\kappa$) are therefore exponential functions – smooth and smaller in magnitude than the total derivatives ($d\omega_S/d\lambda$ & $d\kappa/d\lambda$). In particular, $|(\partial F/\partial\rho_S)(\partial Q/\partial\omega_S)| \ll |d\omega_S/d\lambda|$ and $|(\partial F/\partial\omega_L)(\partial P/\partial\kappa)| \ll |d\kappa/d\lambda|$. Hence

$$\frac{d\rho}{d\lambda} \ \propto \ \frac{d\omega_S}{d\lambda} \ + \ \frac{d\kappa}{d\lambda} \tag{2}$$

This conclusion is also confirmed empirically [2].

To derive an explicit analytical result connecting the surface reflectance to either canopy leaf area index or absorbed radiation, we consider the case of an optically dense canopy of lambertian, horizontal leaves. Canopy reflectance in this case is also lambertian. The canopy reflection function F can be expressed analytically and the partial derivative $\partial F/\partial\omega_L$ can therefore be evaluated

$$\frac{\partial F}{\partial\omega_L} \ = \ \mathrm{L} \ \left[\frac{1}{B}\ \Phi^-(\rho_S, X) \ - \frac{A}{B}\ \Phi^+(1, V)\right] \ = \ \mathrm{L}\ \left\{\frac{\partial F}{\partial\omega_L}\right\} \tag{3}$$

$$\Phi^\pm(x,y) \ = \ \frac{\partial W}{\partial\omega_L}(Wxe_1 + \frac{x}{\mathrm{L}}e_2 \pm ye_1) + \frac{1}{\mathrm{L}}\frac{\partial y}{\partial\omega_L}\left[\exp(\pm p) - \exp(\mp p)\right] \tag{4}$$

where $e_1 = \exp(p) - \exp(-p)$, $e_2 = \exp(p) + \exp(-p)$, $p = W\mathrm{L}$, ρ_S is soil hemispherical reflectance and L is leaf area index [W, X and V are defined in den Dulk [3]. The derivative $d\kappa/d\lambda$ is, with $\kappa(\alpha) = (1-\alpha)\exp(-\alpha) + \alpha^2\ \mathrm{E}_1(\alpha)$ [4],

$$\frac{d\kappa}{d\lambda} = \sum_{i=1}^{N} \wp_i \left[\frac{d\tilde{a}_i}{d\lambda}\left[\exp(-\alpha_i)(\alpha_i - 2) + 2\alpha_i \mathrm{E}_1(\alpha_i)\right] - \tilde{a}_i \exp(-\alpha_i)\right] = \sum_{i=1}^{N} \wp_i \Psi(\alpha_i) \tag{5}$$

where $\alpha_i = \wp_i\tilde{a}_i$. Here $\mathrm{E}_1(\alpha)$ is exponential integral of order one and, α is the absorption coefficient given by the product of absorber concentration per unit leaf area $\wp$ and absorber specific absorption coefficient $\tilde{a}$. Since, N species may be active at wavelength λ, $\alpha(\lambda) = \sum_i^N \wp_i\tilde{a}_i(\lambda)$. In view of Eqs. (3) and (5), the spectral derivative for the case of an optically dense canopy of lambertian, horizontal leaves can be written as

$$\frac{d\rho}{d\lambda} \ \equiv \ \frac{\partial P}{\partial\kappa}\ \left\{\frac{\partial F}{\partial\omega_L}\right\} \ \sum_{i=1}^{N} \ \mathrm{L}_i\wp_i \ \Psi(\alpha_i) \tag{6}$$

Here L_i is the total leaf area per unit ground area, over which the ith-absorber species is distributed. Consequently, $\mathrm{L}_i\wp_i$ denotes the concentration of the ith-absorber species per unit ground area. Therefore

$$\frac{d\rho}{d\lambda} \ \propto \ \sum_{i=1}^{N} \ \mathrm{L}_i\wp_i \ \propto \ \sum_{i=1}^{N} \ \mathrm{L}_i\wp_i\tilde{a}_i \tag{7}$$

that is, the spectral derivative is indicative of the abundance and activity of the various absorbers pertaining to radiation absorption. If only one major absorber species, such as chlorophyll, is of interest, as it is in the case of vegetation remote sensing and if this species is uniformly distributed over the entire leaf area, then $\mathrm{L}_i \wp_i \equiv \mathrm{L}$, where L is the green leaf area index. And, $\tilde{a}_i \equiv \tilde{a}$, the chlorophyll absorption coefficient. Thus,

$$\frac{d\rho}{d\lambda} \propto \mathrm{L} \propto \mathrm{L}\tilde{a} \tag{8}$$

with $\mathrm{L}\tilde{a}$ denoting radiation absorbed by the chlorophyll in green leaves. This, then, is the theoretical basis for relating reflected radiations with canopy leaf area index, and the absorption of photosynthetically active radiation.

REFERENCES

1. R. B. Myneni, S. Maggion, J. Iaquinta, J. L. Privette, N. Gobron, B. Pinty, M. M. Verstraete, D. S. Kimes, and D. L. Williams, "Optical remote sensing of vegetation: Modelling, caveats and algorithms," *Remote Sens. Environ.*, vol. 51, pp. 169-188, 1995.
2. R. B. Myneni, F. G. Hall, P. J. Sellers, and A. L. Marshak, "The interpretation of spectral vegetation indices," *IEEE Trans. Geosc. Remote Sens.*, vol. 33, pp. 481-486, 1995.
3. J. A. den Dulk, "The interpretation of remote sensing, a feasibility study," PhD Thesis, p. 145, The Agricultural University of Wageningen, Netherlands, 1989.
4. S. Jacquemoud and F. Baret, "PROSPECT: A model of leaf optical properties spectra," *Remote Sens. Environ.*, vol. 34, pp. 75-91, 1990.